Brain Tumor Detection Using Convolutional Neural Network and Transfer Learning Approach

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Abstract: **A tumor can be any extra and uncontrolled growth of cells in the body. The brain tumor is one of the deadliest diseases because of the structural complexity and functioning of the brain. It is crucial to identify the brain tumor at an initial stage. MRI is one of the popular imaging modalities used in the field of biomedical imaging as it provides good contrast images. The advancement in imaging using CAD and deep learning makes tumor diagnosis easy. This paper proposes a comparative study between two deep learning models: CNN and transfer learning-based deep learning models. A dataset from the publicly available platform Kaggle is used consisting of 5712 images. The input image is first pre-processed using a Gaussian filter, then segmentation is done by using snake segmentation. Then, the segmented image is again de-noised by using PNLM filters. In the end, both the classifier models are compiled, trained and compared in terms of accuracy, precision, recall and F1-score.**

Keywords—Brain Tumor, Feature Extraction, Classification, Deep Learning, Convolutional Neural Network

I. INTRODUCTION

A lump or group of abnormal cells in the brain is referred to as a brain tumor. The skull in which the brain is housed is highly solid. Any form of tumor growth in this constrained space results in numerous issues. Brain tumors can be divided into two basic categories: malignant and benign. The skull enlarges from the inside when pressure is given to a growing benign or malignant tumor. This cancerous growth can be fatal and harmful to the brain. Brain tumors are divided into primary or secondary types [1]. Tumors that occur in the brain are called primary brain tumors and such kinds of tumors are usually benign. The secondary brain tumor arises due to the spread of cancer cells from another organ to the brain, which includes the lungs or breast. Brain tumors can be originated in the brain itself or they can be spread to the brain from any part of the rest of the body.

The growth rate and status of a brain tumor investigate its effects on nervous system function. The nature, size and location of a brain tumor help doctors determine the treatment process. Depending on the size, location, and rate of tumor growth, brain tumors can exhibit a wide range of signs and symptoms. Many people who have a brain tumor experience new or altered headache patterns, headaches that frequently get worse, nausea, vomiting, vision problems like double vision or loss of peripheral vision, body balance problems, loss of sensation or movement in the arms or legs, confusion about daily activities and behavioural changes [2].

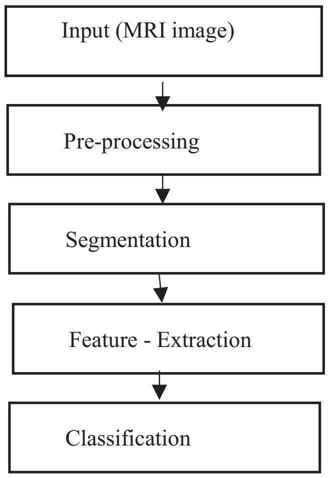

Fig. 1 Brain Tumor Detection Phases

Due to the complex anatomy of the human brain, the identification of brain tumors and their classification by using MRI is a tricky job. There are various steps involved in brain tumor detection using image processing. Following are the details of the various steps applicable for brain tumor detection as shown in Figure 1:

i. Input Image (MRI): This is the very first step in identifying a brain tumor. Several brain MR images are collected from the MRI image database in this step.

ii. Pre-processing: This step increases the chances of detecting the suspicious area. The goal of this stage is to enhance minute image details [3]. Noisy medical MR scans usually have low accuracy. Typically, MR images are corrupted by a smooth signal intensity alteration. This variation reduces the high-frequency image properties

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including its edges and contours and also makes images blurry. Pre-processing is mostly used to reduce image noise and boost contrast levels to obtain better-quality images.

iii. Segmentation: The segmentation of the tumor and the brain tissues around it can give doctors a clear understanding of the spread of the tumor and further analysis can assist in a course of treatment [4]. For diagnosis and treatment, it is crucial to precisely segment brain tumors. First, gliomas can develop in any area of the brain and come in a variety of sizes and shapes. Blurred image content and undetectable boundaries are caused by MRI images' susceptibility to noise and other reasons. Segmentation helps to get the region of interest which is required for further analysis.

iv. Classification: The task of classifying brain MR images for automated tumor detection is fairly challenging. If there is any tumor in the image, that information must be included in the classification stage. A variety of machine learning and deep learning classification algorithms are available that can be used to classify images. In machine learning models, relevant features are extracted from the segmented portion of the images by using techniques like GLCM and wavelet transform method but in deep learning models the feature extraction step is merged with the classification stage as there is no need to extract the handcrafted features from the images as deep learning models are capable enough to learn features from images by their own. Support vector machines, decision trees, and artificial neural networks are some common classification techniques for detecting brain tumors. Below is a brief explanation of each of these algorithms:

(a) Support Vector Machine (SVM): A supervised machine learning model is referred to as a support vector machine model. Regression and classification problems have been solved with this model [5]. Finding a hyperplane that can classify the data is the main goal of SVM. Referred to as decision boundaries, hyperplanes aid in categorising the data points. Support Vectors are data points that are closer to the hyperplane and have an impact on the hyperplane's position and orientation.

(b) Decision tree classification: Decision trees are a type of classification method used in supervised learning for image categorization. It mixes many scenarios for selection using a tree structure and once all options have been exhausted, provides the correct response. A decision tree has nodes and directed edges. There are two different kinds of nodes: internal nodes and leaf nodes. The feature properties are represented by internal nodes. A class is represented by a leaf node. Decision trees' directed edges show the results of feature attribute tests. Small data sets can be classified very successfully using decision trees because the classification accuracy is dependent on the number of trees.

(c) Artificial neural network classification: A large number of neurons are set up and connected to form a simulated neural network structure using the Artificial Neural Network (ANN) method which describes the human brain's neural network structure into a mathematical model [6]. Data set training is used to determine each neuron's weight parameters. According to the process of creating a network model, ANN may be separated into two stages: the training and learning stage and the recognition and classification stage. To increase the precision and speed of image identification and classification, the image training set first adjusts and optimizes the network parameters.

II. Literature Review

Gunasekaran Manogaran, et al. (2019) suggested a technique to analyse the under and over-segmented areas of brain tumors which is called an enhanced orthogonal gamma distribution-based ML (machine-learning) technique [7]. This allowed abnormalities to be automatically discovered in the ROI. The recommended method was developed on a benchmark medical image library for autonomously identifying cancer or normal regions. The testing findings showed that the suggested technique produced improved accuracy for detecting brain tumors by about 99.55%.

Muhammad Sharif, et al. (2019) established an approach in which BSE (brain surface extraction) technique was exploited to extract the skull region from an image [8]. Thereafter, PSO (particle swarm optimization) deployed the skull-removed image for segmenting the images. The extraction of LBPs (Local Binary Patterns) and other relevant attributes from segmented images was the focus of the following phase and the best attributes were chosen using a genetic algorithm (GA). In the end, classification techniques such as ANNs (artificial neural networks) and others were used to categorize the cancer grades. The outcomes showed that the established methodology outperformed the conventional algorithms with 100% accuracy.

D. Rammurthy, et al. (2020) developed a method which is optimization-driven and recognized as WHHO (Whale Harris Hawks optimization) to identify the brain tumor based on MR (Magnetic Resonance) images [9]. Additionally, the segments were used to extract features like mean, variance, kurtosis and LOOP (Local Optical Oriented Pattern). To identify the brain tumor, the DeepCNN (deep convolutional neural network) technique was used. The accuracy, specificity and maximum sensitivity of the WHHO-based DeepCNN were calculated and found to be 81.6%, 79.1%, and 97.4%, respectively.

Md Khairul Islam, et al. (2021) introduced a more advanced method for detecting brain tumors using the PCA (principal component analysis) algorithm and the TK-means (template-based K-means) algorithm [10]. Superpixels and PCA were initially used to extract the important features. A filter was then taken into consideration to improve the image which increased accuracy. The image was ultimately segmented using TK-means to locate the brain tumor. The outcomes of the experiments showed that the new technique provided greater precision and quicker execution.

Md. Ahasan Kabir, et al. (2020) designed an algorithm for detecting the tumor based on SVM (support vector machine) and ANN (artificial neural network) [11]. This algorithm had diverse phases in which gradient intensity smoothing was done to preserve the edge, the image was enhanced, SVM was employed to segment an image, features were extracted and classification was done. The outcomes showed that the designed algorithm provided an accuracy of 97.7% in comparison with other algorithms.

Neelum Noreen, et al. (2020) investigated a technique of multi-level feature extraction to diagnose the brain tumor at initial phases [12]. Two pre-trained models called Inception-v3 and DensNet201 to validate the investigated technique. The softmax classification algorithm exploited these attributes so that the brain tumor was classified. The features were extracted from distinct Dens Net blocks using subsequent models. The investigated technique acquired an accuracy of 99.34% with the initial model and 99.51% with another model while diagnosing the brain tumor.

Ming Li, et al. (2019) developed a Multi-CNN that combined multimodal information with the CNN (convolution neural network) method to detect brain tumors [13]. First of all, the multimodal 3D-CNN made the deployment of extended 2D-CNN. An enhancement of the loss function was then carried out. The feature learning of the lesion region was improved by taking into account the weighted loss function. The results of the tests supported the efficiency of the suggested technique for identifying brain cancer lesions.

Ahmed H. Abdel-Gawad, et al. (2020) recommended a strategy for identifying the edges of the brain tumor from an MR (Magnetic Resonance) image of the brain of a patient [14]. The BCET (Balance Contrast Enhancement Technique) was used to enhance the image's features while providing the superior attributes of medical pictures. Later, using an adequate training dataset and the GA (Genetic algorithm) edge detection technique, the fine edges were discovered. The results proved that the recommended strategy was more effective in comparison to the conventional techniques.

Weiguang Wang, et al. (2020) suggested a technique which was developed based on integrating CNN (convolutional neural network) with MRI (Magnetic Resonance Imaging) technology to detect brain tumors [15]. The efficacy and rate of recognizing the tumor were enhanced and the artificially selected features were put together with features of ML (machine learning) using a convolutional layer. Afterwards, the features were fused to optimize the diagnostic results. At last, the suggested technique was computed in the experimentation. The experimental results revealed the applicability and practicality of the suggested technique.

Ahmed S. Musallam, et al. (2022) developed a revolutionary DCNN (Deep Convolutional Neural Network) model for identifying cancer as glioma, meningioma, and pituitary in addition to a three-step pre-processing strategy to enhance the quality of MRI (Magnetic Resonance Imaging) pictures [16]. The technique of normalizing the batch was implemented to train the technique at a high learning rate. Thus, the layer weights were initialized easily. The accuracy acquired from this technique was computed as 98.22%. The experimental outcomes exhibited that the formulated technique helped boost the accuracy of detecting brain tumors in a short time.

Arkapravo Chattopadhyay, et al. (2020) projected an algorithm to segment the brain tumors from 2D (two-dimensional)-MRI (Magnetic Resonance Imaging) images of the brain after the implementation of CNN (convolutional neural network) and DL (deep learning) models [17]. In addition, TensorFlow and Keras were applied to compare this algorithm against others. The projected algorithm offered an accuracy of up to 99.74% in comparison to the other techniques.

Nivea Kesav, et al. (2021) established a new framework to classify brain tumors and their category based on the RCNN (Region-based Convolutional Neural Network) method [18]. A Two CNN model with an accuracy of 98.2% was initially used to categorize the MRI (Magnetic Resonance Imaging) samples as glioma and normal MRI samples. This model was then put into practice as the framework's feature extractor to identify tumor locations in the Glioma MRI sample. The established framework offered lower execution time in contrast to the other methods at a confidence level of 98.8%.

Saroj Kumar Chandra, et al. (2020) devised a fractional technique to detect and segment the benign brain tumor areas [19]. The Crank-Nicolson technique was adopted to deal with the unconditional stable nature of this technique. An alternate direction implicit finite difference system was exploited in this technique. BRATS dataset was considered to analyze the efficiency of the devised technique. The developed method was compared to traditional algorithms in a comparative analysis. The results validated the adaptability of the devised technique for detecting and segmenting the low variational area. Moreover, this technique offered higher accuracy.

Gajendra Raut, et al. 2020 established a CNN algorithm to detect brain tumor [20]. The initial task was to augment the brain MRI images to increase the volume of the dataset for deep learning (DL) networks. This algorithm was focused on pre-processing the images to eliminate noise and make the images appropriate for further stages. These images were utilized to train the system for classifying newly input images as tumor images or healthy brain images based on extracted features. The backpropagation (BP) algorithm was utilized to alleviate errors and create more precise outcomes. Auto-encoders were employed on generated images to eliminate the redundant features and segment the tumor area based on the K-Means model. The proposed algorithm was proved effective with higher accuracy.

R. Sankaranarayaanan, et al. (2023) emphasized investigating a solution for dealing with the issue related to centralized data collection [21]. The Visual Geometry Group (VGG 16) model was utilized as a tool to diagnose the brain tumor based on a convolutional neural network (CNN) algorithm and determine the metrics for training the model. This model was employed for analyzing the MRI images so that the brain tumor was spotted. The testing outcomes depicted that the developed model was more useful as compared to the traditional methods. Furthermore, this model attained an accuracy of 92% in detecting the brain tumor precisely.

Praveen Kumar Ramtekkar, et al. (2020) proposed an automatic system in which the MRI images of the infected brain were utilized for diagnosing and classifying brain tumors with the deep learning (DL) method and CNN [22]. In this, the images were preprocessed and segmented, features were extracted, and the tumor was detected, classified and localized. The integration of CNN was done with the Gray Scale Co-occurrence Matrix (GLCM) to extract the tumor area, the Partial Differential Equation (PDE) method was implemented to cluster the image and K-means and Otsu thresholding techniques were used for segmenting the image. The images were enhanced through multi-histogram equalization (MHE). The proposed algorithm offered an accuracy of 99%.

Muhammad Aamir, et al. (2023) constructed a less labour-intensive method which detected the brain tumor from MRI scans [23]. A less complex algorithm was utilized for improving the visual quality of an image. The normal areas were removed from the images by morphological operations. The methods of segmenting and clustering the images were employed to recognize the tumor areas. For this, multiple deep neural networks (MDNNs) were deployed. Moreover, an adaptive fusion network (AFN) model was utilized for generating a hybrid feature vector and this vector was employed with multi-class SVM for classifying brain tumors. The constructed method was proven resilient and offered an accuracy of up to 98.98%.

R. S. Mahamed Najeeb, et al. (2022) introduced a DL model for detecting brain tumors on the Kaggle data set. The data was pre-processed and augmented to improve the classification rate [24]. The brain tumor image was classified into different classes after extracting important features from MRI slices. For this, the evolutionary algorithm and reinforcement learning (RL) with the help of TL were used. U-Net and ResNet algorithms were adopted to do multi-classification of the brain tumor. The outcomes demonstrated that the introduced model yielded higher efficiency over other methods. Moreover, the initial algorithm offered 80.0% accuracy and the latter one provided 90.2%.

Amghot Harichander Lal, et al. (2022) developed a DL-based CNN algorithm to detect brain tumors. Firstly, the brain tumor was localized using KMC [25]. Secondly, the developed algorithm was utilized to classify the brain tumor considering GLCM, DWT and statistical colour features to make the system effective. Lastly, this algorithm assisted in classifying brain tumors into benign and malignant. The experimental results reported that the developed algorithm was more efficient as compared to the traditional methods.

Thirumagal E., et al. (2020) designed FCSE-GAN (Feature Concatenation based Squeeze and Excitation-Generative Adversarial Network) to segment the brain tumor region in MRI [26]. The ResNet was executed as a basic NN model. The feature concatenation method was employed with a generator to create sharp MRI images and Squeeze and excitation block with a discriminator to segment the brain tumor. A dataset collected from Kaggle was used for conducting the experiments. The experimental outcomes exhibited that the designed approach was suitable to enhance accuracy, precision, recall and F1-score in comparison with the conventional methods

Oussama Bouguerra, et al. (2022) presented a system to detect brain tumors and classify the binary data. Some training datasets were exploited for computing the deep TL [27]. The fundamental emphasis was to extract the information regarding the brain and classify the tumor as benign or malignant. Three methods of enhancing the clinical image were adopted for training the presented system. According to analysis, the TL model detected the brain tumor reliably on small datasets. The presented system offered an accuracy of 99.77% for classifying brain tumors as compared to existing methods.

Table 1 shows the work already done by other authors in the past few years in the same field.

Table 1. Table showing work done by various authors in past years

Author	Year	Technique Used	Dataset	Findings	Limitations
Gunasekaran Manogaran, et al.	2019	Orthogonal gamma distribution-based ML technique	benchmark medical image database	The suggested technique yielded an accuracy of about 99.55% in detecting brain tumors.	This technique was ineffective in the case of real-time diagnosis.
Muhammad Sharif, et al.	2019	BSE (brain surface extraction) technique	RIDER and BRATS 2018	The results depicted the superiority of the established approach over the traditional algorithms an accuracy of 100%.	This technique did not detect sub-structures of tumors such as solid, or necrotic.
D. Rammurthy, et al.	2020	WHHO (Whale Harris Hawks optimization)	BRATS and SimBrats	The accuracy, specificity and maximum sensitivity of the WHHO-based DeepCNN were calculated to be 81.6%, 79.1%, and 97.4%, respectively.	The scope of this work was limited to this algorithm only.
Md Khairul Islam,	2021	TK-means algorithm and PCA	BRATS dataset	The introduced technique offered a higher accuracy and a reduced execution time.	This technique was applied only to small datasets.
Md. Ahasan Kabir, et al.	2020	SVM (support vector machine) and ANN (artificial neural network) based technique	BRATS	The designed algorithm provided an accuracy of 97.7% in detecting the brain tumor.	The accuracy of the designed algorithm was not able to detect all the phases of brain tumor.
Neelum Noreen, et al.	2020	Inception-v3 and DensNet201	three-class brain tumor dataset	The investigated technique acquired an accuracy of 99.34% with the initial model and 99.51% for another while detecting the brain tumor.	This technique was ineffective on a dataset containing a large volume of images.
Ming Li, et al.	2019	Multi-CNN	MICCAI BraTS 2018	The presented algorithm was effective in locating the lesions of brain tumors.	The presented algorithm did not detect some brain abnormalities in some cases.
Ahmed H. Abdel-Gawad, et al.	2020	BCET (Balance Contrast Enhancement Technique)	RIDER	The results proved that the recommended strategy was more effective in comparison with the conventional techniques.	The accuracy of this strategy was mitigated by the increasing noise level.
Weiguang Wang, et al.	2017	CNN (convolutional neural network)	GBM data set	The experimental results revealed the applicability and practicality of the suggested technique.	The scalability of this technique was reduced in the case of corrupted images.
Ahmed S. Musallam, et al.	2022	DCNN (Deep Convolutional Neural Network)	BRATS	The formulated technique helped boost the accuracy of detecting various diseases of the brain in a short time.	This technique was ineffective in diagnosing the tumor from X-ray, computed tomography (CT), and ultrasound images.
Arkapravo Chattopadhyay, et al.	2020	CNN (convolutional neural network)	BRATS	To identify the brain tumor, the predicted algorithm provided an accuracy of up to 99.74%.	The issue of overfitting occurred in this algorithm.
Nivea Kesav, et al.	2021	RCNN (Region-based Convolutional Neural Network)	Figshare and Kaggle	The established framework offered lower execution time in contrast to the other methods at a confidence level of 98.8%.	It was unable to segment the tumor area pixel-wise.
Saroj Kumar Chandra, et al.	2020	A fractional technique	BRATS dataset	The results validated the adaptability of the devised technique for detecting and segmenting the low variational area at higher accuracy.	The computing cost of this technique was found higher.

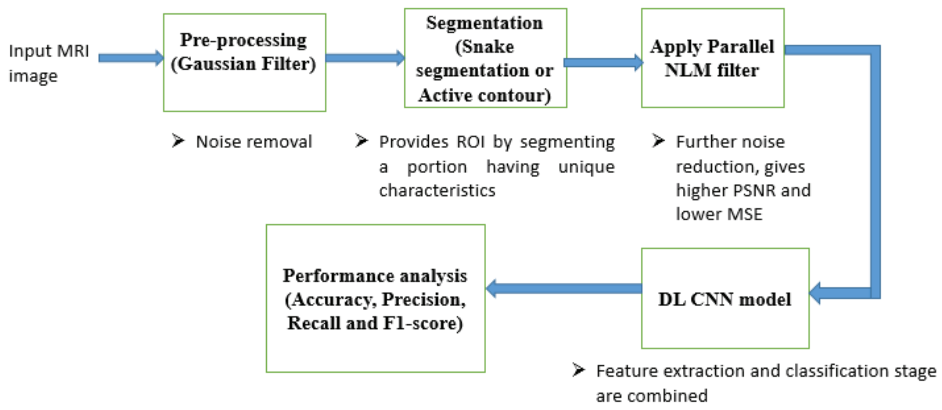
Gajendra Raut, et al.	2020	CNN algorithm	BRATS dataset	The proposed algorithm was proved effective with higher accuracy. Precise outcomes were obtained	The cost incurred is high by the use of autoencoders
R. Sankaranarayaanan, et al.	2023	VGG 16 model	BRATS dataset	The algorithm worked better in comparison to the standard methods that are currently used, with an accuracy of 92%.	Before utilizing this model, it needs to be evaluated on a large dataset
Praveen Kumar Ramtekkar, et al.	2020	CNN (convolutional neural network), Deep Belief Network (DBN)	Few Manually collected images	The algorithm was able to detect, classify and localized the tumor well with an accuracy of 99%	Only a single feature vector is used with CNN. It needs to be evaluated on a larger feature vector
Muhammad Aamir, et al.	2023	Multiple Deep Neural Networks (MDNNs)	BRATS Dataset	The algorithm generated a hybrid feature vector and performed well in classifying brain tumors with an accuracy of 98.9%	The complexity of the model is high
R. S. Mahamed Najeeb, et al.	2022	RF learning and transfer learning method, U-Net and Res-Net algorithm	Kaggle dataset	The algorithm yielded higher efficiency and provided an accuracy of 90.2%	The dataset taken was limited and small.
Amghot Harichander Lal, et al.	2022	K-means clustering, GLCM, DWT, CNN	BRATS dataset	The algorithm outperformed all the other traditional methods compared in the paper.	The proposed model was able to classify between only two classes of tumors.
Thirumagal E., et al.	2020	FCSE-GAN and Res-Net algorithm	Kaggle dataset	The proposed algorithm improved accuracy, precision, recall and F1-score when compared with the conventional methods	The algorithm mainly focuses on the segmentation phase only.
Oussama Bouguerra, et al.	2022	Deep learning models and Transfer learning	BRATS Dataset	The presented system offered an accuracy of 99.77% for classifying brain tumors as compared to existing methods.	The algorithm was executed on a small dataset.

III. Methodology

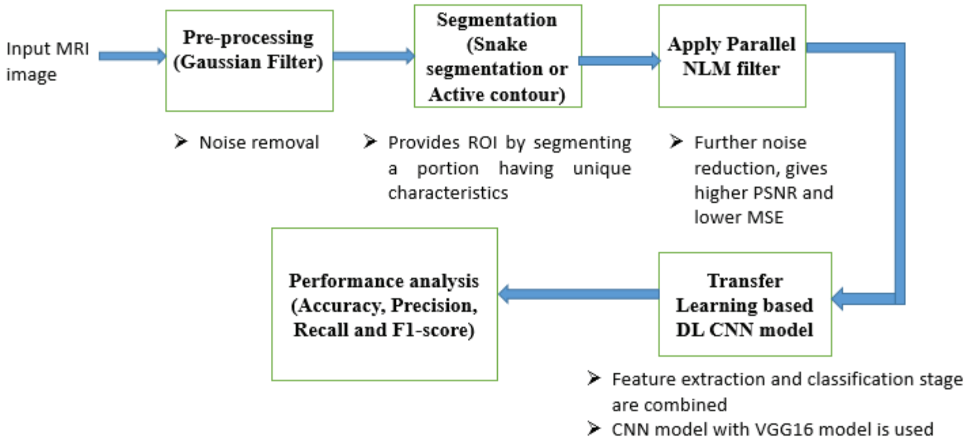
The work is based on comparing the results obtained from two techniques of brain tumor detection. In the whole process, the MRI image is taken as input which is pre-processed using a Gaussian filter, technique of snake segmentation is applied for the segmentation, to remove extra noise from the segmented part non-local means filter is applied and in the last two techniques have been used and thus implemented two different models based on deep learning. The two techniques (as shown in Figure 2) used are:-

(i) Convolution neural network (CNN)

(ii) Transfer learning-based deep learning approach



(i) CNN model



(ii) Transfer learning based deep learning model

Fig. 2 The 2 implemented framework for Brain Tumor Detection

The method of brain tumor detection using deep learning techniques is divided into various phases which are explained below: -

1. **Input MRI image and Pre-processing: -** The MRI image is used as the input. A dataset from the publicly available platform Kaggle was used which comprised 5712 images. It is an authenticated source. This Dataset consists of four classes of tumors namely Glioma, Meningioma, No-Tumor and pituitary. The entire dataset is split into two subsets which are the training set and testing test in the ratio of approximately 80:20. The models are trained using the training set and tested by using the testing set. A Gaussian filter is used to pre-process the image. MRI images are generally good contrast images and contain a very small amount of noise in them. The noise in the image can easily be reduced using the Gaussian filter. This filter, also referred to as a smoothing operator, causes images to become smooth in texture. This filter eliminates fine visual features that are inherently present [28]. Its impulse response is a Gaussian function that depicts the noise's probability distribution. Gaussian noise is effectively eliminated by this filter. It is a non-uniform, linear, low-pass filter with a specified standard deviation Gaussian function.

2. Segmentation:- The technique of snake segmentation will be applied which can accurately and precisely segment the brain region part from the MRI image and provide the region of interest (ROI). The Snake active contour segmentation technique is inspired by the raster scan which will cover the maximum edges of the image. An image segmentation algorithm which is based on the deformation model is called the snake active contour model. The Snake active contour model starts with an initial contour in the image space. It iteratively searches and adapts to the points of minimum energy state and provides the best contour detection. It is also associated with a characterizing energy function that describes the shape of the region which the snake traces. The energy function depends on internal and external energy. The properties of the curve itself dictate the internal energy. The characteristics relevant to the image define the external energy. Under the restrictions of the inner and outer energies, the starting contour curve

$$\mathrm{C}(s) = \big(\mathrm{x}(s), \mathrm{y}(s)\big), s \in [0,1]$$

begins to converge continuously to the boundary of the target area by minimizing the energy functional:

$$E(C) = \int_0^1 \Big(\alpha E_{int}\big(C(s)\big) + E_{img}\big(C(s)\big) + \gamma E_{con}\big(C(s)\big)\Big)\, ds \ldots\ldots\ldots (1)$$

The energy function is made up of three parts: E_{int} stands for internal energy, E_{img} for image energy, which is set by desired target position characteristics like edges and E_{con} for constrained energy, which is typically a curve. The Snake active contour model's key benefit is that it fully takes into account the geometric restrictions.

3. Filtering:- The snake segmentation method is the best-automated segmentation method but sometimes introduces a little noise in the segmented image at the boundary region which can be de-noised using a parallel non-local mean filter which is the advanced version of a non-local mean filter. The PNLM filter gives a lower MSE (Mean Square Error) value and a higher PSNR (Peak Signal to Noise Ratio) value as compared to the NLM filter. A strong similarity measure that takes into consideration the pixels surrounding the pixel being compared is used by the NL-means filter to compute a weighted average of surrounding pixels and restore every pixel in the image. The output of a non-local means (NLM) filter is a weighted average of the pixels within a sizable search window, with higher weights given to pixels with similar nearby patterns.

4. Classification:- Here, the two approaches are being used.

(a) CNN model:- The convolutional neural network is initially utilised during the classification stage. Convolutional layers, pooling layers and fully connected layers are used in the CNN model. In convolutional layers, Relu is employed as the activation function, whereas Softmax is used as the activation function on the output side. The time and resources required to train the model grow as the network's hidden layer count rises. Figure 3 shows the implemented model architecture of CNN indicating the sequence of various layers and no. of filters used.

(b) Transfer learning based deep learning model:- In this model the concept of Transfer Learning is used. As the base model, the pre-trained model "VGG 16" is used to identify and classify the tumor if present in the input test image. VGG16 is Visual Geometry Group and 16 here symbolises that it has 16 learnable parameters [29]. It belongs to the Department of Science and Engineering of Oxford University and was first came forward in 2014 in the ILSVRC competition. Transfer learning approach helps in reducing the time and resources used to train the model. Out of the 16 layers of VGG16 architecture, here 13 convolutional layers integrated with the CNN model are used. Along with this, pooling layers, ReLU activation function, many filters of different sizes and softmax activation function are also used in building this model. Figure 4 shows the architecture of the implemented Transfer learning-based deep learning model. The entire dataset is divided into a ratio of approximately 80:20 as the training and testing dataset. During the model compilation, ADAM is used as the optimizer for the optimization of the parameters. The entire training is done in four epochs. The batch size of 20 is selected among the many different possible batch sizes. The parameter alpha has to be selected very carefully because if it is very large, then the model doesn't conclude to a final output and if it is too small, then the model takes too much time to conclude. So, the learning rate of alpha is selected as 0.0001 to avoid the same. The loss and metrics used for evaluation are sparse categorical cross entropy and sparse categorical accuracy [30].

5. Performance Analysis:- In the last, the performance of both models will be tested in terms of certain parameters. The evaluation metrics will be Accuracy, Precision, Recall and F1 score.

1. Accuracy:- It is the ratio of the number of correct predictions made by the model over all kinds of possible predictions made by the model.

$$A_i = (\mathrm{TP} + \mathrm{TN}) / (\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}) \ldots\ldots\ldots(2)$$

where, TP = True Positive = Part of the positive class that is correctly predicted

TN = True Negative = Part of the Negative class that is correctly predicted

FP = False Positive = Part of the positive class that is incorrectly predicted

FN = False Negative = Part of the negative class that is incorrectly predicted

2. Precision:- It is a measure that tells us what proportion of images that the system diagnosed as having a tumor, actually had a tumor.

Precision= TP/ (TP+FP) = TP/ (Predicted Yes)… (3)

3. Recall (Sensitivity, TPR):- Recall is a measure that tells us what proportion of images that had a tumor was diagnosed by the algorithm as having a tumor.

Recall= TP/ (TP+FN) = TP/ (Actual Yes)….. (4)

4. F1 score- It is a trade-off between the precision and recall.

F1- score=2*(recall*precision) / (recall +precision)…. (5)

IV. Experimental Set-up

The implementation of the models has been done in Google Colab where the Python codes can be easily written and saved in the online storage of Google Drive. Colab offers 12 GB RAM, 50GB hard drive space and free GPU access to its users. Firstly the dataset is loaded. Then the models are defined and compiled. The models are then trained and evaluated in terms of the parameters like accuracy, precision, recall and execution time.

V. Result and Discussion

Following pre-processing, segmentation is done. After the segmentation stage, the image is then filtered using the PNLM filters which are used for de-noising the images. The various authors have proposed techniques for the brain region segmentation but they are unable to achieve low MSE value. Here, an advanced version of NLM filters is used which is called a Parallel Non-Local Mean filter. Table 2 shows the value of PSNR and MSE after the Gaussian filter and PNLM filters. The PNLM filter improves the PSNR value and reduces the MSE value which is required for better image processing. The dataset is collected from the publicly available Kaggle platform. It consists of 5712 images and four classes which are Glioma, Meningioma, Pituitary and No Tumor. Accuracy, precision, recall and F1-score are considered here to test the models.

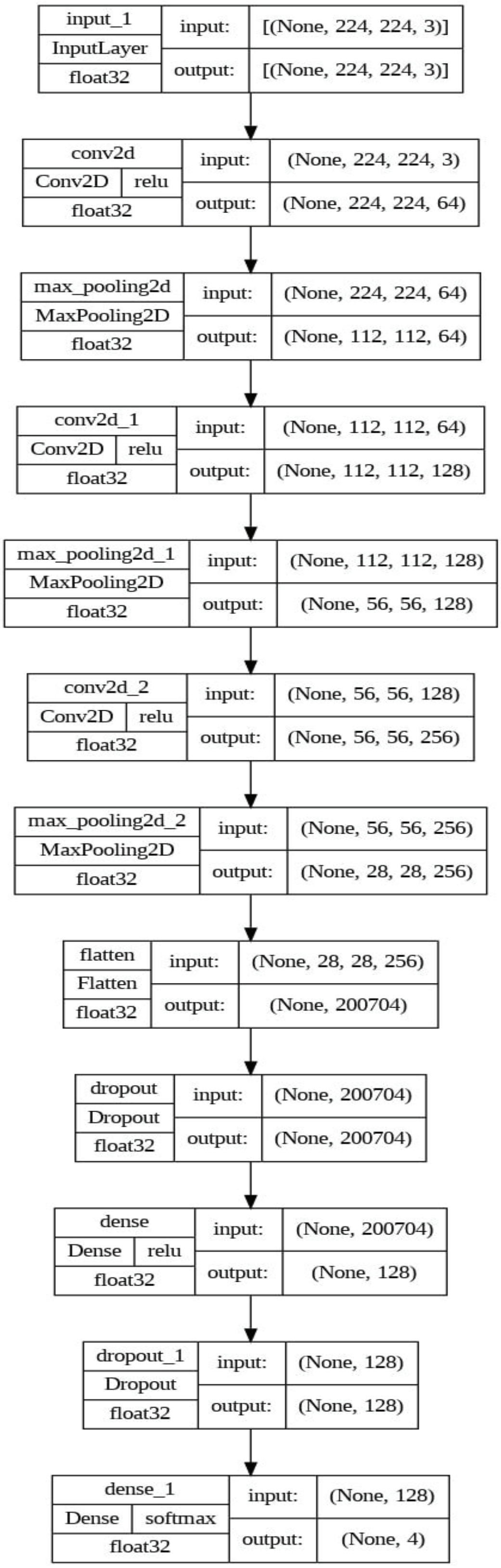


Fig. 3 Architecture of CNN Model

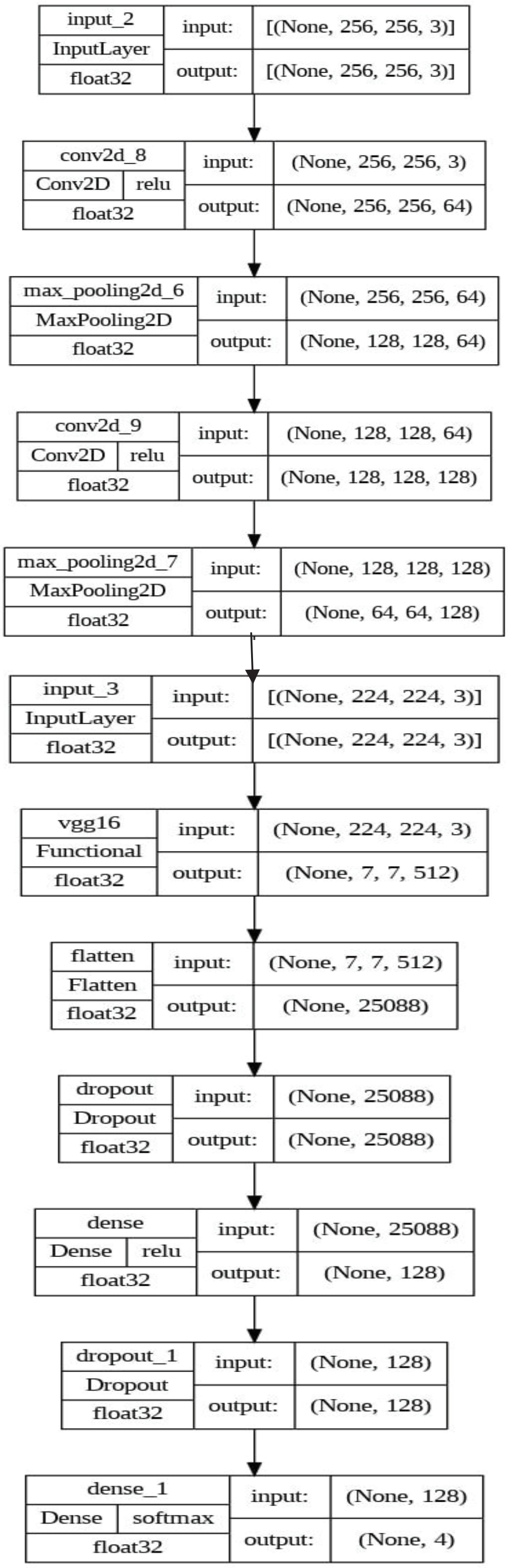


Fig. 4 Architecture of Transfer learning based deep learning model

Table 2. PSNR and MSE value

	PSNR	MSE
After Gaussian filter	11.1149	5030.2278
After PNLM filter	70.1649	0.0063

Table 3. Dataset distribution

No. of MRI Images in the dataset		
Brain images	**Tumor class**	**No. Of images available**
Normal	**No tumor**	**1595**
Abnormal	**Glioma**	**1321**
	Meningioma	**1339**
	Pituitary	**1457**
Total		**5712**

As shown in Table 3, the dataset has four classes and data is almost balanced with approx. Equal number of images in the distribution of each class. The classes are quite balanced and no overfitting problem occurs at the time of prediction.

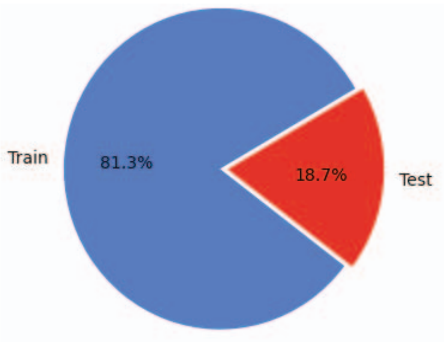


Fig. 5. Splitting of dataset

Figure 5 shows that the dataset has been split into training data and testing data approximately in the ratio of 80:20.The training of both the models is done in 4 epochs. The training history of both models are shown. For the CNN model, it is shown in figure 6 that the loss has been reduced from 0.7058 to 0.2139 whereas the training accuracy has been increased from 71.37 % (in the first epoch) to 90.14% (in the fourth epoch). Similarly, for the transfer learning based deep learning model, it is shown in figure 7 that the loss has been reduced from 04141 to 0.0744 whereas the training accuracy has been increased from 84.67 % (in the first epoch) to 97.36% (in the fourth epoch).

Fig. 6. Training history of CNN model

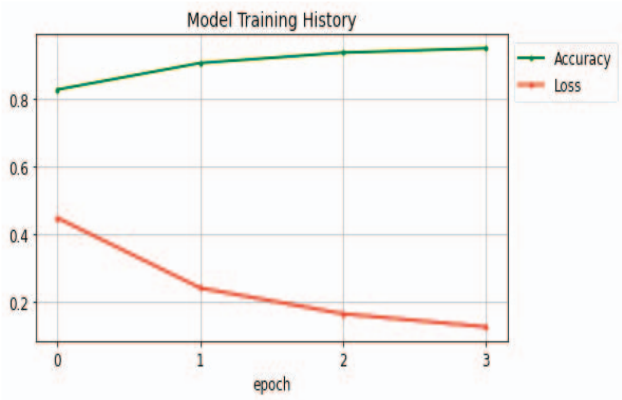


Fig. 7. Training history for Transfer learning based deep learning model

The confusion matrix for both the models are shown here in Figure 8 and 9. From the figure, it is clearly shown that in the CNN model, only 270, 253, 398 and 295 images are correctly classified for the four types of labels that are used in the dataset such as Glioma, Meningioma, No tumor and pituitary respectively and for the transfer learning based DL model 272, 299, 403 and 294 images are correctly classified for the four types of the labels that are used in the dataset such as Glioma, Meningioma, No tumor and pituitary respectively. As shown in Table 4, the testing accuracy for the CNN model is obtained as 92.75% and for the transfer learning-based deep learning model is 96.72% (approximately 97%). The accuracy score shows that the transfer learning-based DL model outperforms the CNN model. Figure 10 shows the analysis done for the CNN model. Figure 11 shows the analysis done for the transfer learning-based deep learning model. The precision, recall and F1-score are also improved for the transfer learning-based deep learning model.

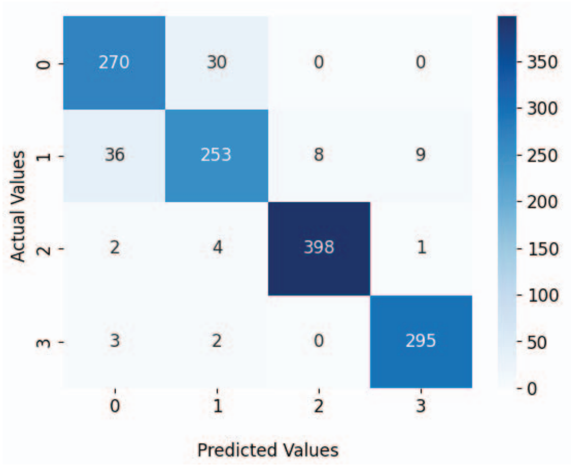


Fig. 8 Confusion matrix For CNN

(where 0= Glioma, 1= Meningioma, 2= No Tumor, 3= Pituitary)

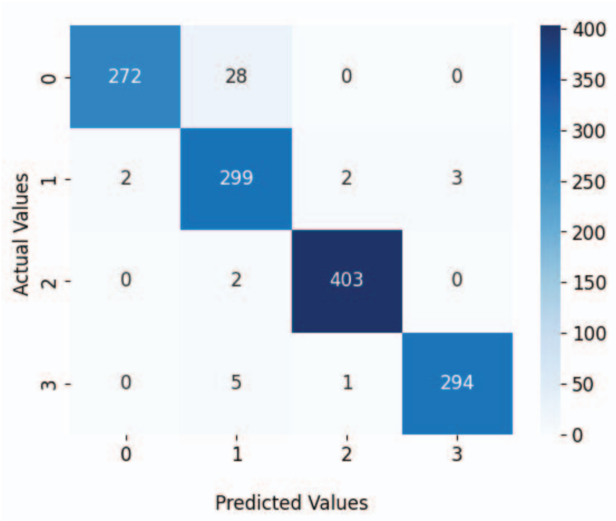


Fig. 9 Confusion matrix For Transfer learning based DL model

Table 4. Results obtained

	CNN model			Transfer learning based CNN model		
	Precision	Recall	F1- score	Precision	Recall	F1- score
Glioma	0.87	0.90	0.88	0.99	0.91	0.95
Meningioma	0.88	0.83	0.85	0.90	0.98	0.93
No -Tumor	0.98	0.98	0.98	0.99	1.00	0.99
Pituitary	0.97	0.98	0.98	0.99	0.98	0.98
Accuracy score	92.75%			96.72%		

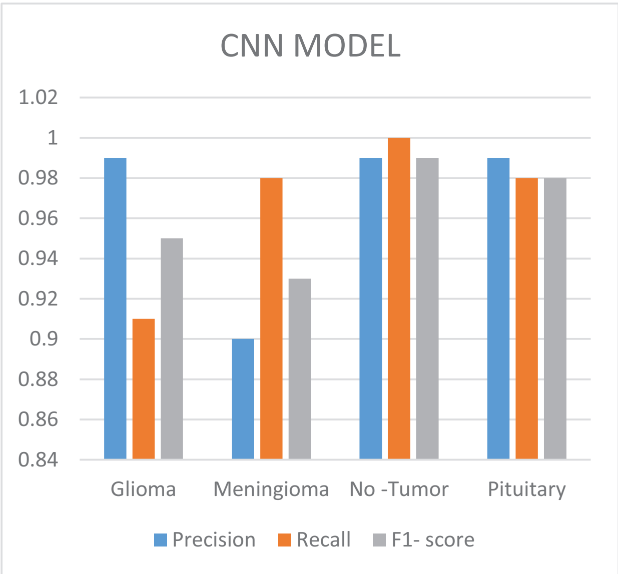


Fig. 10. Analysis of CNN model

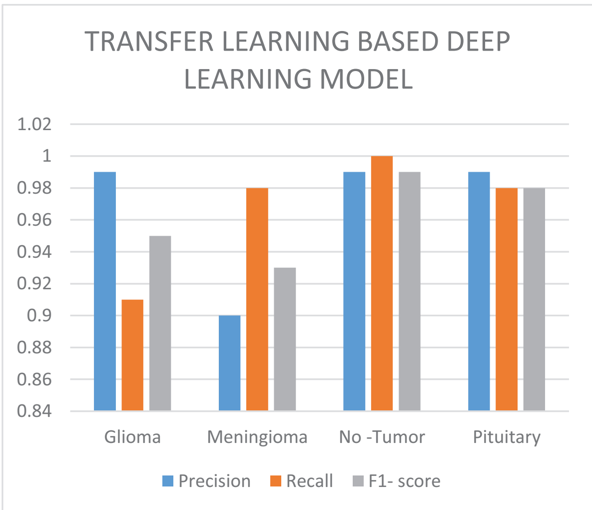


Fig. 11. Analysis of transfer learning based deep learning model

CONCLUSION

The essence of the research work presented in this paper is the detection of brain tumors from MRI images. Medical image processing is growing popular day by day owing to a variety of disease detection and prediction methods. Brain tumor detection consists of many steps called pre-processing, segmentation, de-noising and classification. Here, Gaussian filters are used for pre-processing the input image, snake segmentation method is used for segmenting the image to get the required ROI. Further, the PNLM filters are used for de-noising the segmented region and then for classification, two methods are used which are convolutional neural network and transfer learning-based deep learning model. After analyzing the results obtained, it is found that the concept of transfer learning is very helpful as it reduces the demand for resources which are utilized for retraining the model. The performance parameters used are accuracy, precision, recall and F1-score. When both models are compared based on the above metrics, the transfer learning-based deep learning model shows better results.

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