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REVIEW PAPER ON BRAIN TUMOR MRI DETECTION USING CNN

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Abstract

There has been an upsurge in the number of cases of brain tumors in both adults and children in recent years. A brain tumor can be treated if the diagnosis and treatment are given on time. Thus, researchers and scientists are working towards developing a technique and method for identifying the type, location and size and stage of tumor. Deep learning is a branch of machine learning (ML) which has been very successful in lots of sectors, especially in the medical field because it can handle a lot of data. MRI images may now be used to diagnose brain tumors with remarkably high accuracy in terms of tumor kind and size due to deep learning and convolutional neural networks. The major goal of this study is to give a complete assessment of existing research and findings in identifying and classifying brain tumor by means of MRI scans. The study's findings will help researchers compare previous studies to future ones, as well as give an idea of the usefulness of various deep learning (DL) and machine learning (ML) methods.

Keywords: Brain Tumor, Deep Learning, Machine Learning, Convolutional Neural Network (CNN).

Introduction

The structure of brain contains millions of cells and is complex. Rapid growth of cells is the cause of brain tumor. Brain activity can be affected by the uncontrolled growth of cells and executes disruption of the normal function of brain cells which can cause death if not identified early and accurately. Tumor is a fibrous net of unwelcomed tissues developed within our body. Tumors can be classified on two grounds malignant or benign. The benign form can be easily distinguished with the slow growth rate and has a definite border. Malignant are treated as Cancerous tumors. They are very pugnacious and fatal in nature which are very difficult to notice. Malignant tumors can also affect the other areas of spinal cord and brain. 18,600 adults [1] death due to brain tumor every year can be treated as most dangerous tumor. The use of imaging technology can help in the assessment of brain anatomy. Magnetic Resonance (MRI) scans can be helpful to identify the location of the tumor in the brain. Therefore, there is a need for automated system that can be able to diagnose the tumor in MRI without human intervention. CNN is used for image recognition and are commonly used to analyze visual images. Classification done through CNN are fast and efficient. CNN can be used for image classification and applied in MRI to detect brain tumor. Image classification is the method of taking an input in the form of pictures and outputting a class means which object image is this or showing the probability of the input of a particular class.

Difference between CT- Scan, X-Ray MRI

A kind of radiation therapy called X-Ray that involves passing rays through the human body. X-Rays can easily see dense objects like human bones, but light dense objects are difficult to see, making it difficult to diagnose bone degeneration, tumor placement, and fractures.

CT scan Diagnosis can be done through taking pictures of inside body through various angles using x-rays These pictures can be combined through computer into a detailed 3-D image which shows abnormalities or tumors in the brain. CT scan can also be helpful in diagnosis of bleeding and development of fluid filled spaces in the brain referred as ventricles. CT scan accuracy of brain tumor detection is 82.60%. CT scan uses radiations which are harmful to the brain and can increase the chances of cancer. The chances of cancer can be increased if there is a repeat exposure of scans over a long period of time. Doctors always advice for MRI.

MRI can be able to yield a detailed information in the form of slices associated regarding healthy and tumor region. Due to numerous slices it always be a challenge to check for tumor abnormalities. These slices are analyzed one by one through clinical experts which is a time taking and challenging process. The identification of a tumor in all slices is quite difficult. An exact identification of brain tumor is the need of expert radiologist.

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There is a step by step process to detect the abnormalities in the brain. The procedure[1] is as follows:-

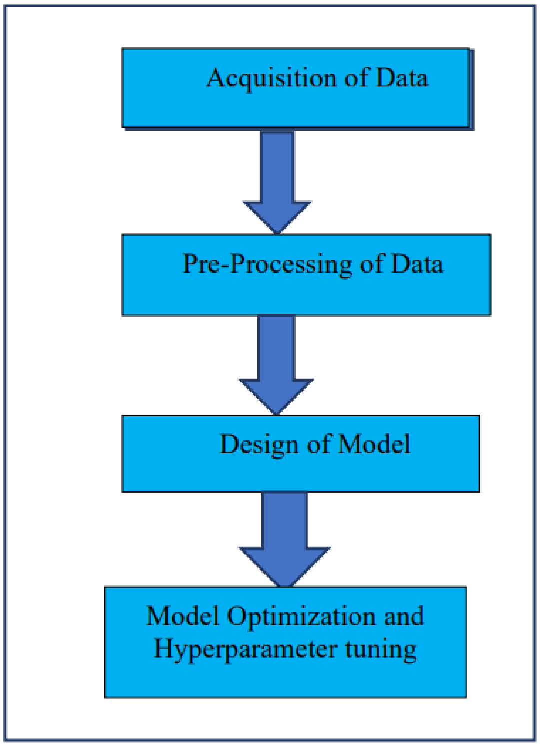

Figure 1: Flow of Control of Methodology for Brain Tumor Classification

Data Acquisition: Obtaining the dataset for the development of our system. After obtaining the dataset then recognize from them the normal brain and abnormal brain with tumor. From the dataset one can also differentiate the type of Tumor. Which will help in prescribing the medicine.

Data Pre-processing: The purpose of preprocessing is to enhance the quality of the MR film and convert it to a format suitable for computer imaging. Pre-processing is also helpful in filtering the images and improve certain other parameters like improvement in visual aspect of MRI, improvement in signal noise ratio, unrequired part from the background can be cropped, making image evener and holding the edges. The skull striping activity can also be performed for removing all non brain tissues like skin, fat and skull from the brain image. Skull striving can be done through the techniques like image contour, histogram analysis or a threshold value and morphological operation and segmentation.

Model Design: MRI images required by the doctors to diagnose needs to be extremely précised and accurate examination. Overhead cost can be increased by Examining such images and an expert doctor needs to be required. Accuracy and efficiency can be increase by applying CNN model architecture.

Hyper-Parameter Tuning and Model Optimization: The variable that can be use to define the network structure or the total number of hidden units and the variables which can determine the training of network or the learning rate are known as Hyper parameter. Hyper parameter has to be set before optimizing weights and bias. Methods that can be use to find out hyper parameter are Manual search, Random Search, Bayesian Optimization, Grid search. Model performance can be improved through good hyper parameter combination. Some open source libraries are available to automatically tune the hyper parameter. Tensor flow and Keras Tuner are vastly used open source library to tune the hyper parameter.

The main aim of this review is to provide an assessment of the research being done previously and identify the best algorithm to detect brain tumor by means of MRI scans and classify them in the category on the basis of type of brain tumor. The type of brain tumor will be helpful to start with the early treatment in case if it is a cancerous brain tumor the chances of recovering will be more and tumor cannot be harmful to the patient. So the objective of this study is to find out the among various machine learning and deep learning algorithm will diagnose the harmful tumor at early stage which will helpful to the doctors for not being harmful and can be recovered.

Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNN) is an enhanced architecture of artificial neural networks (ANN) where the features of visual cortex are used and can be used in the classification of images. Obtaining the input image as a pixel array is the primary aim of image classification. The image is processed through a sequence of convolutional, nonlinear, pooled and fully connected layers, after which the output is generated. CNN's Layer Architecture [2] as mentioned below:

1. The top layer is called the input layer.
2. To extract features from the input layer, a convolutional layer is employed. To extract features, numerous different filters are applied as filters.
3. To reduce the dimension, pooling layer is employed that is the input for consequent layer and placed after the convolutional.
4. To recognize pattern of features instead of middle layers fully connected layer is used.
5. The network's last layer is the classification layer.

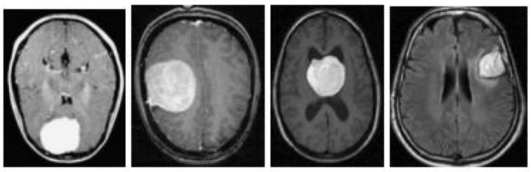

Figure 2: Tumor Brain

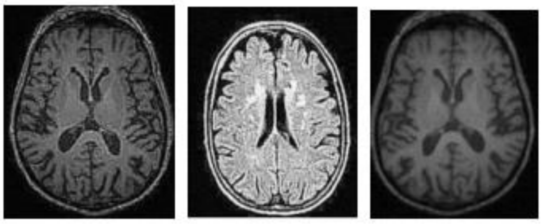

Figure 3: Non Tumor Brain

Literature Review

The authors [3] applied the hybrid method for classifying and detecting the brain tumor imaging (MRI) using the BRATS 2015 database where two types training (110 cases) and testing with (220 cases) in his research study. His finding was able to classify brain images in two categories as malignant and benign tumor by applying supervised hybrid SVM and CNN approaches. The outcome indicates the highest accuracy classified with PPV (positive predictive Value) and FPV (False Predictive Value) with lowest and at the same time the total achievement was 98.495 percent classified appropriately with the help of hybrid model, the SVM had given accuracy rate 72.5536% and CNN alone gave 97.4394%. According to author hybrid model was the most improved and effective techniques for classification. The improvement can be seen by applying the Faster CNN with SVM in future. Although the size and accurate position of the tumor also have an impact for classification.

In the study by [4] had been analyzed for detecting the region comprising tumor and classify the region into 3 tumor categories i.e. meningioma, glioma and pituitary. They utilized faster R-CNN which is a deep learning approach and executed through Tensor Flow library. They applied the technique on dataset which is publicly available consisting of 3,064 images of 32 patients (708 meningioma, 1426 glioma, 930 pituitary) for the classifier's training and testing. The accuracy of the observation was 91.66%, which is more than the work done previously on same dataset.

The authors [5] used the BRATS2013 dataset to train six CNN models, which were tested with clinical MRI volumes ranging from V01 to V08 Volumes V01 and V02 was from non tumor categories. Model 4 provided the optimum outcomes out of the six models tested. Model 1 recognized 43 percent and 16% of slices as tumor slices from V01 and V02 volumes of non-tumor cases respectively, after training with the dataset of BRATS2013 and testing was done with clinical dataset. The improvement in accuracy was seen in model 6 as compared to model 1 with accuracy rate of 96%-99%. Limitation was with the proposed model was that it was taking more time for execution which can be reduced by GPU (Graphic processing unit).

The researcher [6] had proposed a technique which consist of 4 phases lesion enhancement, selection for classification and feature extraction, segmentation and localization. Wavelet filter had been used for noise reduction then inceptionv3 pre trained prototype applied to extract feature and informational attribute had been chosen employing a non-dominated sorted genetic algorithm (NSGA). Tumor slices were sent to the YOLOv2-inceptionv3 model for tumor region localization after optimized features had been sent for classification. In this way, features from the depth-concatenation(mixed-4) layer of the inceptionv3 model were retrieved and provided to YOLOv2. For segmenting the actual tumor area, the localized images were forwarded using McCulloch's Kapur entropy approach. On BRATS 2018, RAT2019, and BRAT2020 for tumor detection, the techniques were validated and achieved a 0.90 estimate score in segmentation, classification and localization of brain wounds. The enhanced hybrid technique in real-time can be used to detect brain tumors that are still in their premature stages. Using a quantum computation approach, this research might be expanded to include the study of brain tumors.

CNN had been used by the researcher [7] to detect brain tumor through brain tumor MRI. They compare the result of various classifier algorithms used in CNN with the Softmax fully connected layer. The accuracy obtained by Softmax classifier was 98.67% which was more than other classifier. In addition to accuracy the researchers were also emphasized on sensitivity, precision and specificity evaluate the network performance. They created a new approach based on feature extraction techniques using Convolutional Neural Network (CNN) to achieve a 99.12 % accuracy rate on test data. The work had been done on the 153 patients MRI images contains normal and images with brain tumors both. There were 86 females and 68 males among the 153 patients, who ranged in age from 8 to 66. 1892 images were obtained from 153 patients, training was done on 1666 images and testing was done on 226 images. The initial size of collected images were 512 × 512.

Three hybrid CNN model was presented by the researchers [8] namely Res-SegNet, U-SegNet and

SegUNet, with the goal of accurately segmenting brain tumors from MRI scans with high accurateness. The most prominent CNN models for semantic segmentation, U-Net, SegNet, and ResNet, were included in projected model. The size of brain tumor is so small that are at times missed during down sampling leading to incorrect segmentation. Such form of drawback is solved by incorporating a skip association into the SegNet, that was inheritable from and Res-Net18 and U-Net. The BRAT dataset was used to train and evaluate the CNN models. Mean accuracy, weighted IOU, Global accuracy, mean IOU, and BF-Score were used for evaluation for segmentation accuracy. Mean accuracy was achieved 91.6% with U-SegNet, 93.3% with Res-SegNet and 93.1% with Seg-UNet.Training of hybrid model require more time due to more number of layers and more trainable parameters connected with hybrid architecture. Post network training, the segmentation of brain tumor is being done by system automatically from MRI scans within a short time span. In future, various filter sizes and all MRI images methods might be used to improve tumor segmentation results, and by increasing mini batch sizes from 16 to 64 and max-expoch from 80 to 120 can be able to improve segmentation results.

The authors [9] had used CNN model to identify the brain tumor using MRI scans. The Resnet architecture was worked as the base architecture. The bottom 5 layers of Resnet50 were eliminated in the suggested model, and 8 additional layers were added, yielding a 97.2 percent accuracy rate. Comparative analysis had been done with InceptionV3, Alexnet, Desnsenet201, Resnet50 and Googlenet models and observed that proposed model had given the highest performance for classifying brain tumor images which the most effective in detecting brain tumor.

The researchers [10] had introduced algorithm based on deep learning (kernel based CNN) combined through M-SVM for automatic segmentation of tumor efficiently. By using the Laplacian of Gaussian (LoG) filtering technique, contrast limited histogram equalisation (CLAHE), and feature extraction based on the tumor's shape, position, features on the surface, and shape within the brain, the researchers improved the MRI scans and formed them more aesthetically appealing. On the basis of selected features for image classification M-SVM was used. In the proposed method, the accuracy of brain tumor segmentation was around 84%. This method can be helpful in the early diagnosis of a brain tumor, which can helpful to the patient to avoid death.

The authors [11] created a 3D CNN (convolutional neural network) architecture in which the brain tumor was first extracted for feature extraction before passing it through a pre-trained CNN model called VGG19. The correlation- based approach is used as a selection approach for the extracted attributes, which resulted in the selection of the best features, which were then validated for final classification using a feed-forward neural network. The 2015, 2017 and 2018 of BRATS dataset were used for validation, experimentations and obtained an accuracy of 98.32, 96.97 and 92.67% respectively. From low contrast MRI scan images, the proposed architecture accurately segments the tumor. When pre trained model was trained by extracting images of tumor the classification accuracy of tumor type classification was increased. At the same time the time for classification was also increased as matched with trained pre trained model by original MRI images. According to authors the deep reinforcement model can provide the better result for brain tumor classification.

The researchers [12] had proposed the system that is based on K-means clustering combined with Fuzzy C-Means (KMFCM) and an active contour by level set is used for tumor segmentation. Effective segmentation methods like Edge detection and intensity were used which can detect brain tumor very easily. The active contour method in conjunction with the level set method was used in the suggested system for efficient segmentation. The parameters of white pixels, black pixels, processing time, and tumor identified area were used to evaluate the system's performance. With bigger number of segmentation difficulties and a quicker execution time, this technique ensures high segmentation quality. For measuring accuracy, specificity, similarity index values, and sensitivity, tumor size and tumor area length can be determined from vertical and horizontal positions. This information is useful for the physician in effective diagnosis in treatment of tumor. Intensity adjustment process can help in improving segmentation accuracy.

Differentiation among meningioma, glioma and pituitary tumors through 3-class classification was done by the authors [13] which are the common brain tumors type . The recommended classification method used the pre-trained GoogleNet and the deep transfer learning concept for feature extraction from brain MRI images. The experiment employed the Figshare dataset, and the dataset of MRI scans underwent a five-fold cross-validation technique on a patient-level. The proposed system had given 98% accuracy of mean classification. Other performance measures evaluated in the study included precision, F-score, recall, and specificity, under the curve (AUC). Transfer learning was observed to be useful technique when medical images availability was limited with the fewer training samples.

To improve segmentation performance, the authors [14] first enhanced the resolution of MRI images by adopting a super resolution (SR) approach in the suggested method. Segmentation of MRI images was done with Fuzzy-C-Means (FCM) approach. For feature extraction and tumor image segmentation, the researchers employed SqueezeNet, a recent CNN architecture. Classification was performed by Extreme Learning Machine (ELM). A small neural network model with lesser parameters was used for feature extraction. Despite having a 98.33 percent accuracy rate, the rate of brain tumor recognition using Fuzzy-C Means without SR was 10% higher. The performance of this method varied based on the training dataset.

The authors [15] had built an ACNN (Artificial Neural Network) based model which take MRI and analyzed them using mathematical formulas and matrices operations to find out the chances of brain tumor. Training was done over MRI images. The dataset was from Kaggle, out of 253 images 155 were healthy images and 98 with tumor. With the help of data augmentation, it was expanded to 14 times larger. The model had given the result of predicting of tumor with the accuracy rate of 96.7% in validation data and 88.25% on test data.

The researcher [16] proposed a novel CNN model that incorporated the pre trained AlexNet, hypercolumn method, VGG-16 networks, Support Vector Machine (SVM), and Recursive feature elimination (REF). The advantages of this combined model were that local discriminative features could be preserved using the hypercolumn approach, which could be extracted from layers at various levels of the deep architectures. The simplification capabilities of VGG-16 and AlexNet Networks both by combining the deep features can be attained through the last fully connected layers of network was exploited from the proposed model. The discriminative capacity was enhanced by using REF and was able to discovered the most effective deep features. The dataset used in the model was 155 tumors and 98 normal brain MRI which was taken from 253 patients. Although JPEG format of MRI images of the dataset was not having high resolution and each individual image had dissimilar resolution. Accuracy rate of 96.77% was achieved through proposed model without the use of handcrafted feature engine. The model was entirely automated and efficient for classification and very helpful in supporting the expert's decision making process and wrong diagnosis rates was reduced to a greater extent.

The authors [17] presented a new architecture of CNN for the classification of tumor in three brain tumor categories. Developed network was significantly easier to use than the pre-trained tumors that were tested using T1-weighted contrast enhanced MRI. The network performance was evaluated using two 10-fold cross validations with two databases. One of the 10-fold methods: subject-wise cross validation was employed to assess the generalization ability of the network. An augmented picture database was used to evaluate the network's improvement. The record-wise cross-validation for the augmented dataset yielded the best result for 10-fold cross-validation with an accuracy rating of 95.56 percent. The dataset for this model was used 3064 T1-weighted contrast-enhanced MRI scans from Tianjin Medical University's Nanfang Hospital and General Hospital. The new approach with better execution speed and good generalization capability proved that it was an efficient decision support tool for radiologist in medical diagnosis.

For the classification of glioma brain tumors into two groups i.e. Low grade (LG) gliomas and High grade (HG), researchers [18] proposed a fully automatic and effective deep multi-scale 3-D Convolutional neural network architecture using complete volumetric T1-Gado MRI order. The suggested design combines both types of contextual information-local and global-with smaller kernels and reduced weights. An MRI preprocessing method based on intensity normalization and adaptive contrast enhancement was used to deal with data heterogeneity. Data augmentation techniques was used for effective training. Dataset used was BRATS-2018 generated the most discriminatory feature map to separate among LGG and HGG in comparison with 2D CNN variant. Overall accuracy was obtained was 96.49% using the validation dataset with the help of proposed approach and the researchers had concluded that while manipulating CNN-based techniques, appropriate MRI preprocessing and data augmentation may be able to deliver accurate classification.

By employing the Fuzzy C-means clustering method, a conventional classifier, and CNN, the authors [19] suggested a procedure to extract brain tumor from 2D MRI brain images. A real-time dataset containing a range of tumor sizes, shapes, locations and image intensities was employed in the study. They used CNN which implemented by using Tensorflow and Keras and achieved an accuracy of 97.87% which was very good as compared to traditional classifiers. On the basis of texture and statistical data, the researchers were able to differentiate between abnormal and normal pixels.

The authors [20] suggested a semantic segmentation method based on CNN for automatic brain tumor segmentation in 3D brain tumor segmentation. The dataset comprised of four kind of imaging modalities (T1, T1C, T2, Flair). They also did a 3D comparison of the predicted label and ground truth, which included the entire brain. This method was utilised to successfully pinpoint the precise location of the tumor, with images displayed in a variety of planes including sagittal, coronal, and axial. The mean Intersection over Union (IoU) score was 91.718, and the mean BF score was 86.946 and 92.938, respectively, as a result of semantic segmentation. The dice score of the test images demonstrated the closeness between ground truth and expected labels. The dataset used was BRATS, which contained 4 imaging modalities (T1 (T1-weighted), T1C (contrast enhanced T1-weighted), T2 (T2-weighted), and FLAIR), as well as 257 training images with labels and MRI dimensions of 240*240 with 155 slices (Fluid Attenuation Inversion Recovery). To examine semantic segmentation for tumor prediction and background, 5 different types of MR imaging were used, and analysis of segmentation matrices such as mean IoU, weighted IoU, and mean BFScore was performed. As a result, it was discovered that 3D imaging and semantic segmentation can both be effective in accurately identifying brain tumors.

The architecture suggested by researcher [21] to overcome the main drawback in the existing technology which require the vast number of parameter with high system specification and high execution time for implementation. Two publicly available datasets were analyzed using a Region based Convolutional Neural Network (RCNN) to suggest an architecture for classifying brain tumors and detecting their tumor types. Figshare (Cheng et al., 2017) and Kaggle (2020). The researcher's goal was to reduce execution time by using a simple framework for the study of brain tumors. The classification of glioma and healthy tumor MRI samples was completed successfully with an accuracy of 98.21 percent using a two channel CNN, a low complicated architecture The tumor region is constrained using bounding boxes and the same architecture in the later feature extraction of an RCNN for detecting the region of a glioma MRI sample that has been classified from the preceding stage. The techniques were extended to encompass the two new tumor types of meningioma and pituitary tumor with a comparatively short execution time compared to other existing architecture, with an average confidence level of 98.83 percent.

A CNN-based strategy was developed by the authors [22], then classical classifiers and deep learning techniques were used, for segmenting brain tumors from 2D MR brain images (MRI). To train the model, different images with various tumor locations ,sizes, shapes and image intensities were taken. Implementation SVM on CNN provided very low accuracy of only 20.83%. An accuracy of 98.10 percent was provided by switching the last layer to Softmax and the optimizer to AdaMax. Change of optimizer from Adamax to RMSProp had given the output accuracy of 99.74%. The implementation of proposed method was done with “TensorFlow” and “Keras” in Python. The study used 273 images for the testing dataset and 2473 images in total for the training dataset in a 9:1 ratio with an 11 epoch method. The proposed approach removes some images to prevent overfitting and uses a 9-layer CNN model with 14 phases.

Result and Implication

Among the various Machine learning and Deep learning algorithm Classification through CNN were able to categorized the tumor in three brain tumor categories which can be able to help the doctors to detect the cancerous tumor and start the diagnosis. The accuracy rates this algorithm was able to provide was 95.56 % with the bigger dataset. Semantic Segmentation method based on CNN can be able to segment the tumor automatically in 3D brain tumor segmentation. In this method four kind of imaging modality was considered i.e. T1, T1C, T2, Flair with 3D comparison of the predicted label and ground truth was done with the whole brain. This method was effective in accurately identifying the brain tumor with 5 different kinds of MRI. The architecture based on RCNN was able to reduce the execution time after applying on two publicly available dataset and easier framework. RCNN method was able to classify glioma and healthy tumor from MRI scans with accuracy rate of 98.21 percent. RCNN method was able to locate the region of the tumor which was helpful to the doctor for starting the treatment at the right location and size prediction can be done to prevent the patient at early stage. The technique was extended to classify two another type of brain tumor meningioma and pituitary tumor with short execution time and 98.83 accuracy rate.

Conclusion

In this paper various traditional classification and segmentation techniques for detecting brain tumor present in the (Magnetic Resonance images (MRI) are reviewed. This review's primary goal is to provide an overview of frequently used techniques for classifying and segmenting brain images. Many meaningful algorithm have been developed till now but there is a lacking in each one in one way or other due to absence of standardization. Till date the techniques used were SVM, RCNN, CNN, six CNN Model, hybrid CNN Model, VGG 16, M-SVM.

Dataset used were BRATS 2013 to 2020, Figshare, Kaggle, images from hospitals. The conclusion drawn from the lengthy analysis presented above is that a fully automatic, unified framework is necessary to accurately and effectively classify brain tumors into a variety of categories with reduced complexity. Among various classification algorithm RCNN method was useful in classifying the type of tumor with shorter execution time and 98.83 percent of accuracy rate with two publicly available dataset. Apart from classification RCNN was able to locate the region of tumor which can be helpful in predicting the size of the tumor.

Conflict of Interest

There is no conflict of interest between the authors in this manuscript.

References

1. S. Sarkar, A. Kumar, S. Chakraborty, S. Aich, J. Sim, and H. Kim (2020). "A CNN based Approach for the Detection of Brain Tumor Using MRI Scans". No. 16580, 16580-16586.
2. R. Hashemzehi, S. J. S. Mahdavi, M. Kheirabadi, and S. R. Kamel (2020). "Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and NADE". Biocybernetics and Biomedical Engineering, 40(3), 1225-1232, doi: 10.1016/j.bbe.2020.06.001.
3. M. O. Khairandish, M. Sharma, V. Jain, J. M. Chatterjee, and N. Z. Jhanjhi (2021). "A Hybrid CNN-SVM Threshold Segmentation Approach for Tumor Detection and Classification of MRI Brain Images". Irbm, 1, 1-10, doi: 10.1016/j.irbm.2021.06.003.
4. E. Avşar and K. Salçin (2019). "Detection and classification of brain tumours from MRI images using faster R-CNN". Tehnički glasnik, 13(4), 337-342, doi: 10.31803/tg-20190712095507.
5. T. Kalaiselvi, S. T. Padmapriya, P. Sriramakrishnan, and K. Somasundaram (2020). "Deriving tumor detection models using convolutional neural networks from MRI of human brain scans," International Journal of Information Technology (Singapore), 12(2), 403-408, doi: 10.1007/s41870-020-00438-4.
6. M. I. Sharif, J. P. Li, J. Amin, and A. Sharif (2021). "An improved framework for brain tumor analysis using MRI based on YOLOv2 and convolutional neural network". Complex & Intelligent Systems, 7(4), 2023-2036, doi: 10.1007/s40747-021-00310-3.
7. M. Siar and M. Teshnehlab (2019). "Brain tumor detection using deep neural network and machine learning algorithm". 2019 9th International Conference on Computer and Knowledge Engineering, ICCKE 2019, no. Iccke, 363-368, doi: 10.1109/ICCKE48569.2019.8964846.
8. D. Daimary, M. B. Bora, K. Amitab, and D. Kandar (2020). "Brain Tumor Segmentation from MRI Images using Hybrid Convolutional Neural Networks". Procedia Computer Science, 167(2019), 2419-2428, doi: 10.1016/j.procs.2020.03.295.
9. A. Çinar and M. Yildirim (2020). "Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture". Medical Hypotheses, 139, 109684, doi: 10.1016/j.mehy.2020.109684.
10. R. Thillaikkarasi and S. Saravanan (2019). "An Enhancement of Deep Learning Algorithm for Brain Tumor Segmentation Using Kernel Based CNN with M-SVM". Journal of Medical Systems, 43(4), 1-7, doi: 10.1007/s10916-019-1223-7.
11. A. Rehman, M. A. Khan, T. Saba, Z. Mehmood, U. Tariq, and N. Ayesha (2021). "Microscopic brain tumor detection and classification using 3D CNN and feature selection architecture". Microscopy Research and Technique, 84(1), 133-149, doi: 10.1002/jemt.23597.
12. P. G. Rajan and C. Sundar (2019). "Brain Tumor Detection and Segmentation by Intensity Adjustment". Journal of Medical Systems, 43(8), 1-13, doi: 10.1007/s10916-019-1368-4.
13. S. Deepak and P. M. Ameer (2019). "Brain tumor classification using deep CNN features via transfer learning". Computers in Biology and Medicine, 111, 103345, doi: 10.1016/j.compbiomed.2019.103345.
14. F. Özyurt, E. Sert, and D. Avcı (2019). "An expert system for brain tumor detection: Fuzzy C-means with super resolution and convolutional neural network with extreme learning machine". Medical Hypotheses, 134, doi: 10.1016/j.mehy.2019.109433.
15. S. Irsheidat and R. Duwairi (2020). "Brain Tumor Detection Using Artificial Convolutional Neural Networks". 2020 11th International Conference on Information and Communication Systems, ICICS 2020, 197-203, doi: 10.1109/ICICS49469.2020.239522.
16. M. Toğaçar, Z. Cömert, and B. Ergen (2020). "Classification of brain MRI using hyper column technique with convolutional neural network and feature selection method". Expert Systems with Applications, 149, 113274, doi: 10.1016/j.eswa.2020.113274.
17. M. M. Badža and M. C. Barjaktarović (2020). "Classification of brain tumors from mri images using a convolutional neural network". Applied Sciences (Switzerland), 10(6), doi: 10.3390/app10061999.
18. H. Mzoughi et al., (2020). "Deep Multi-Scale 3D Convolutional Neural Network (CNN) for MRI Gliomas Brain Tumor Classification". Journal of Digital Imaging, 33(4), 903-915, doi: 10.1007/s10278-020-00347-9.
19. P. V. Rama Raju, G. Bharga Manjari and G. Nagaraju (2019). "Brain tumour detection

using convolutional neural network". International Journal of Recent Technology and Engineering, 8(1), 73-76, doi: 10.22214/ ijraset.2020.6100.

20. M. Feyzi (2021). "Biomedical Signal Processing and Control Brain tumor prediction on MR images with semantic segmentation by using deep learning network and 3D imaging of tumor region". 66, doi: 10.1016/j.bspc. 2021.102458.
21. N. Kesav and M. G. Jibukumar (2021). "Efficient and low complex architecture for detection and classification of Brain Tumor using RCNN with Two Channel CNN". Journal of King Saud University - Computer and Information Sciences, xxxx, doi: 10.1016/ j.jksuci.2021.05.008.
22. A. Chattopadhyay and M. Maitra (2022). "Neuroscience Informatics MRI-based brain tumour image detection using CNN based deep learning method". Neuroscience Informatics, 2(4), 100060, doi: 10.1016/j.neuri.2022.10006 0.