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Brain tumor detection and classification with DGMM – RBCNN technique

Sandhya. U
Assistant professor, Department of ECE, GRT Institute of Engineering and Technology, Tiruttani
Email: sandhya.u@grt.edu.in

K Naresh Kumar
Assistant professor/ECE, GRT Institute of Engineering and Technology, Tiruttani
Email: naresh.kr84@gmail.com

Saranya A P
Assistant professor, ECE, GRT Institute of Engineering and Technology, Tiruttani
Email: saranya.ap@grt.edu.in

N. Jayapal
Assistant Professor, Department of ECE, Kongunadu College of Engineering and Technology, Trichy – 621215, Tamilnadu
jayapal385@gmail.com
Email:

Dr. S. Kumarganesh
Professor, Department of ECE, Knowledge Institute of Technology, Salem-637504, Tamilnadu
Email: skgece@kiot.ac.in

***Abstract*---**Glioblastoma Multiforme, which accounts for 80% of malignant primary brain tumors in adults, is divided into two types: High Grade Glioma (HGG) and Low Grade Glioma (LGG). LGG tumors are less aggressive than HGG tumors, growing at a slower rate and responding to treatment. Because tumor biopsy is difficult for people with brain tumors, non-invasive imaging methods such as Magnetic Resonance Imaging (MRI) have been widely used to diagnose brain cancers. We examine Deep Convolutional Neural Networks (ConvNets) for brain tumor classification utilising multisequence MR data in this paper. Early detection of the tumor is possible with artificial intelligence-based solutions. This manner, a tumor might be detected early and a condition that could risk human life could be resolved. The architecture was used to detect probable brain cancers early, which constitute a serious threat to human life.

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***Keywords*---**Corner Net Model-Faster R-CNN, brain tumor, MRI, Feature Extraction, Segmentation, Gray Level Co-occurrence Matrix.

Introduction

The brain tumor is a fatal disease that kills thousands of individuals each year. A tumor is an abnormal growth of tissues inside the human skull that can damage the nervous system's and body's functionality [3]. According to research conducted by the National Brain Tumor (NBT) Foundation, over 29,000 cases of brain tumors are detected each year in the United States, with roughly 13,000 patients dying each year [4]. Every year, more than 42,000 people in the United Kingdom are diagnosed with a brain tumor. Furthermore, statistics show that these patients range in age, gender, and health, with the tumor occurring anywhere in the brain. Because of its increased soft tissue contrast, magnetic resonance imaging (MRI) has become the primary non-invasive technology for brain tumor diagnosis over the previous few decades. Gliomas account for 80 percent of all malignant brain tumors that originate in the central nervous system's glial cells. The World Health Organization (WHO) divided gliomas into two categories based on their aggressiveness and infiltrative character. Low-grade gliomas (LGG) are a type of glioma that includes both low-grade and intermediate-grade gliomas (WHO). In the United States, in addition to the 700,000 main brain tumor patients, roughly 80, 000 additional cases are diagnosed each year, with nearly 70% of benign tumors and 30% of malignant tumors.

Tumors that have spread to other parts of the body are known as metastatic brain tumors. It was often delivered to the brain via the bloodstream. Cancer is recognised in metastatic tumors. The development of a brain metastatic tumor has impacted around 25% of cancer patients. For example, lung cancer tissue has been shown to influence the growth of a metastatic brain tumor in 40% of individuals with lung cancer. In the past, people diagnosed with such malignancies were only expected to live for a few weeks. Patients' long-term survival rates have improved thanks to more sophisticated diagnostic techniques, novel surgical, and radiation-based therapies. The grades of gliomas can be used to further categorise them. Grade II cancers are similar to grade I tumors in that they grow slowly but can invade surrounding tissues and develop into faster-growing tumors over time. Under the microscope, grade III brain tumors have an odd look. They require medical treatment in addition to surgery since they have a significant proclivity for invading other brain tissues. Finally, Grade IV tumors are the fastest-growing tumors and require the most rigorous treatment (National Cancer Institute 2020). Our model shows how to create an automated approach that can distinguish between normal and abnormal MRI pictures and classify tumors as meningioma tumors, glioma tumors, or pituitary tumors. Brain image segmentation from MRI images is difficult and time-consuming, but it is required for tumor detection and classification, oedema, haemorrhage detection, and necrotic tissue detection. MRI imaging is the most effective imaging tool for early detection of anomalies in brain areas, and it is poised to become a hot topic in medical imaging research in the near future (AlZubi et al., 2011). The following is a breakdown of how this article is structured. The work and development that had been done re cently are discussed in section. The major goal of this research is to use MRI symmetry information to automatically determine the location, boundaries, and kind of tumor. Clinical diagnostics can be used to aid in the detection of brain tumors. The goal is to create a tumor-proof algorithm that combines several techniques to provide a solution for tumor detection in MRI brain imaging. Because it operates over patches using kernels, a CNN has the advantage of taking context into consideration and being used with raw data. The usage of CNNs has also been proposed in the field of brain tumor segmentation. Zikic et al. used a shallow CNN with two convolutional layers separated by stride 3 max-pooling, one FC layer, and a softmax layer, followed by one FC layer. Urban et al. evaluated the use of 3D filters, despite the fact that the majority of authors preferred 2D filters. The 3D character of the photos can be exploited with 3D filters, however this increases the computing effort. We use data augmentation to investigate the significant geographic and anatomical heterogeneity in brain tumors, which is an important problem.

Literature Review and Survey

Convolutional Neural Networks (ConvNets) provide a cutting-edge framework for image recognition and classification [21–23]. The ConvNet architecture is meant to resemble the core workings of the mammalian visual cortex system as closely as possible. The visual cortex has been found to have numerous layers of abstractions that search for specific patterns in the input vision. A ConvNet is constructed on the same principle of stacking numerous layers to learn multiple abstractions of the input data. In 2020, Grovik et al.

[14] used the CNN method to show that multisequence MRI may be used to detect brain metastases automatically. The study included 156 patients with brain metastases who had an MRI. As a consequence, the applied method's area under the curve (AUC) was found to be 0.98. In 2020, Sharif et al. employed CNN- based Inception-v3 architecture to segment brain tumors. In 2020, Hollon et al. used stimulated Raman histology and deep CNN to investigate brain tumor diagnosis. The proposed model had an overall accuracy rate of 94.6 percent. To detect brain cancers, Rehman et al. employed CNN-AlexNet, GoogLeNet, and VGGNet designs in 2020.

The Figshare brain tumor MRI dataset was used to achieve this purpose. The best accuracy rate in the investigation was achieved using the VGG16 architecture, which was 98.69 percent. Khan et al. used CNN architectures to predict brain tumors from MRI in the year 2020. The VGG-16 model had the highest accuracy, with a score of 96 percent. In 2020, Mehrotra et al. used five different CNN architectures to detect brain cancers, including AlexNet, GoogLeNet, ResNet50, ResNet101, and Squeeze Net. The proposed model was

found to be the most accurate, with a score of 99.04 percent. TC Hollon, B Pandian, AR Adapa, E Urias, AV Save, and others Intraoperative diagnosis of brain tumors in near real time utilising stimulated raman histology and deep neural networks (Nature Medicine, vol. 26, 2020). The SVM family of algorithms, which includes Linear, Cubic, and Gaussian kernel functions, was employed for classification. This approach works on the notion of drawing a hyper plane by employing support to maximise the margin between the classes. Three types of kernel functions are utilised to improve the accuracy of the results, and he has identified the damaged area and trained his model to predict the tumor grade using SVM classifier. The taxonomy of tumors was expanded to include two types: primary and secondary tumors. The term "primary tumor" refers to tumors that begin in the brain. Secondary tumors are those that begin in another region of the body and later move to the brain. They are categorised in to two subtypes: malignant and benign. She employed an Artificial Neural Network to classify the main tumor (ANN).
The ANN is made up of numerous nodes. Each node accepts a single input, conducts an operation on it, and then sends it to another layer of nodes, with each node having a node value at the output layer. It essentially learns by receiving feedback. It starts with K cluster centres and reassigns observations to clusters based on how similar the observations are to the cluster centres. Because of the high degree of graylevel similarity in MRI images, automating the detection and segmentation of brain tumors is a difficult challenge. Brain MRI pictures go through a completely automated two-step segmentation process. This study proposes a method for automatically classifying medical images into two categories: normal and abnormal, based on visual attributes and automatic identification of anomalies [13]. Normal and aberrant images are used to determine statistical texture functionality. The image was classified using the KNN classifier [19]. The performance of the KNN classifier versus the kernel-based SVM classifier (Linear and RBF). According to the estimated confusion matrix and outcome, the KNN classification rate is 80% higher than the SVM classification rate.

Methodology for detecting brain tumors based on the Corner Net model proposed (RCNN)

This section shows how the proposed framework for detecting brain cancers is put into action. The goal is to automatically recognise and diagnose the brain tumor for a given input sample without requiring any operator involvement. There are two primary steps to our work: To begin, we prepped the dataset by adding annotations to the input photos to pinpoint the precise position of tumors. The model was then trained using the newly created annotations for tumor classification and localisation. The suggested method is based on a modified CornerNet model that has delivered cutting-edge object localization results. For feature calculation, we used CornerNet with DenseNet-41 as the basis network. During training, the enhanced CornerNet framework receives an input sample as well as the bounding box annotation. DenseNet generates the feature maps that the CornerNet model uses to determine the tumor's class and position. Atlast, accuracies for all units are computed using measures used in image processing methods. The suggested mechanism for tumor detection is shown in Figure 1.

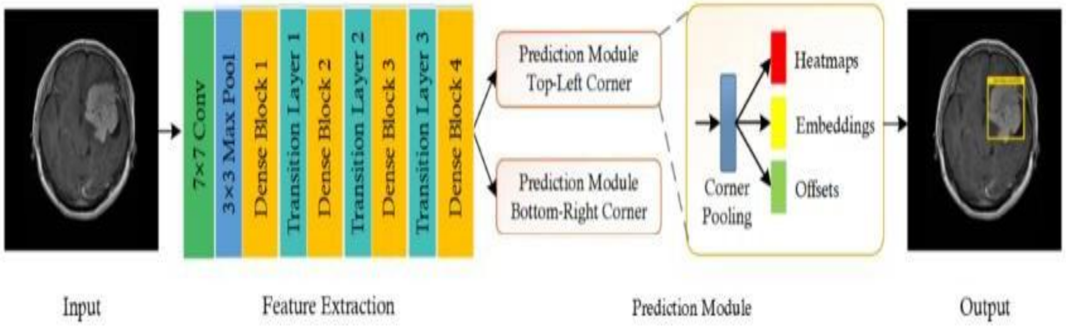

Figure 1. Input, Feature Extraction

Prediction module that generates a bounding box, a confidence score, final Output to locate and classify a brain tumor.

Pre-processing module – Annotations

It is critical to define the exact location of tumors in input photos while training the DL model. We created the annotations with the LabelImg tool for this reason. Figure 2 depicts a selection of the annotated photographs. An XML file comprising details about the tumor and their placement coordinates in the photos is acquired after the annotation process is completed. The XML file is then converted into a training file, which is used to train the model.

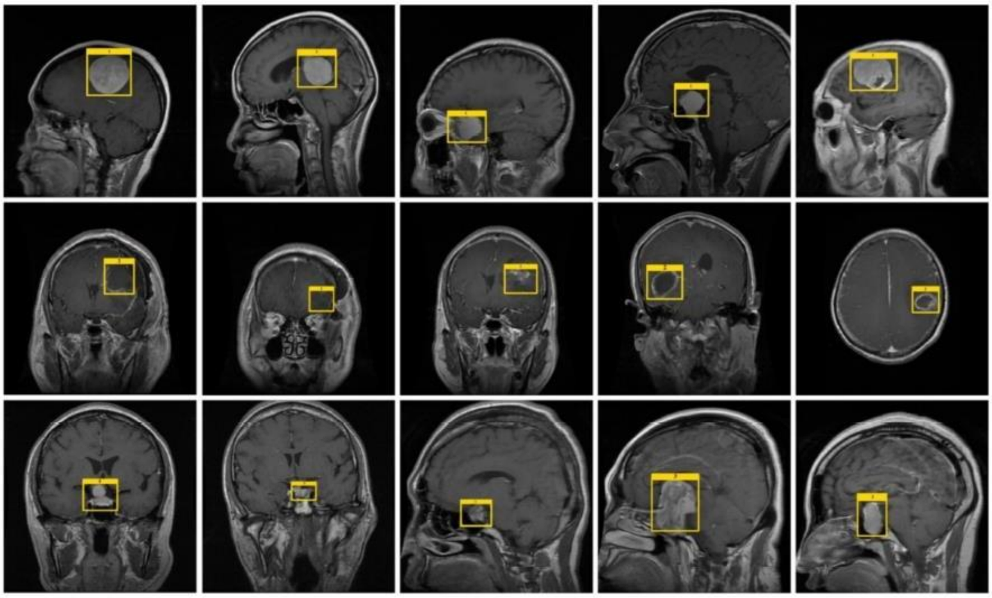

Figure 2. Sample annotated images

Conversion Deep learning & Faster R-CNN

Artificial neural networks are a type of artificial intelligence that tries to learn and adapt in the same way that the human brain does. Deep learning is a multi-layered artificial neural network design with multiple layers in each layer. Because of its numerous processing units, deep learning differs from other artificial intelligence and machine learning methodologies in the literature in that it can respond to data and complex scenarios. Attribute information is provided to the system ahead of time in o ther machine learning methods, but in deep learning, the traits are discovered by the method's skills. Ren et al. presented the Faster R-CNN object identification architecture in 2015. Convolutional neural networks, such as YOLO, are used in the architecture (You Look Only Once). Three neural network layers make up the faster R-CNN. The feature network, region proposal network, and detection network are the three layers (Figure 2). This highlighted network's job is to extract the most important characteristics from images. The output of the feature network preserves the geometry and structure of the original image.

Skull stripping

The first step is to create a skull mask from the MRI image, and the second step is to segment the image into grey matter, white matter, and tumor region using an advanced K-means algorithm improvised by a two-level granularity-oriented grid-based localization process based on standard local deviation, and then to assess the tumor's length and breadth. This study proposes a method for automatically classifying medical images into two categories: normal and abnormal, based on visual attributes and automatic identification of anomalies [13]. Normal and aberrant images are used to determine statistical texture functionality. The image was classified using the KNN classifier [19]. The performance of the KNN classifier versus the kernel-based SVM classifier (Linear and RBF).

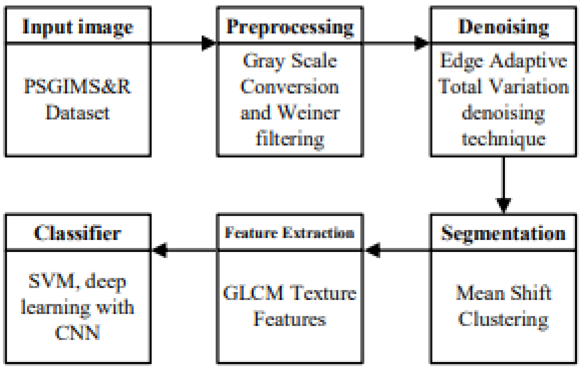

Fig.3. Overview of the CNN system

The MRI picture is used as the input at first, and it is preprocessed using the wiener filter. The wiener filter would blur the image and remove any noise that was present in it. Denoising is performed after the pre- processing stage, using the Edge Adaptive Total Variation approach. The primary goal of denoising is to remove any undesirable signals from the input image. The denoised image is then passed via the Segmentation process, which employs Mean Shift Clustering to group pixels with comparable features. Finally, the clustered output is used to extract features during the feature extraction step, and the extracted features are then used to classify tumors. Deep learning with CNN is utilised in the classification stage of the Support Vector Machine. These are utilised to differentiate between tumorous and non-tumorous MRI pictures. Figure 3 depicts a high- level overview of the proposed system.

Diagnosis histopathological

Despite contemporary medical technological developments, histological evaluation of biopsy specimens is still used to diagnose, classify, and grade brain cancers. Pathological testing is commonly performed after a clinical examination and interpretation of imaging modalities like magnetic resonance imaging (MRI) or computed tomography (CT) to arrive at a conclusive diagnosis. The most well-known drawbacks of this procedure are that it is invasive, consumes more time, and prone to sampling errors. It is possible to improve physicians' and radiologists' diagnostic abilities and reduce the time required for a right diagnosis with the use of computer-aided completely automated identification and diagnosis methods that aim to create fast and precise judgements by specialists.

Segmentation

For brain tumor detection, a segmentation model based on the CNN method was proposed. A preprocessing method was utilised to reduce noises in the proposed model, and two sub -networks were utilized for stepwise modeling. The first network was used to pinpoint the location of the tumor. Following that, the second network categorize the tumor. The researchers used the BRATS 2015 dataset, which contained 220 instances of high-grade glioma and 54 cases of low-grade glioma. A U-Net CNN-based model for detecting brain tumors without the use of radiation was published by Dong et al. in 2017. The study employed the BRATS 2015 dataset, which contained 220 high-grade glioma tumors and 54 low-grade glioma tumors. The investigation proved that the recommended technique was viable. The Bhattacharya coefficient approach for tumor diagnosis on brain MR images was proposed by Chinmayi et al. in 2017. The greatest accuracy rate in the study was 99.1 percent. In 2016, Isin et al. employed the CNN approach to segment brain tumors. The CNN-based technique, which was trained on multimodal MRI brain pictures, produced good outcomes, according to the study. Gliomas, one of the most aggressive kinds of brain tumors, were investigated by Pereira et al. in 2016. The BRATS 2013 dataset was used in the study, and a CNN-based segmentation method was used. Furthermore, combining density normalisation with CNN resulted in more effective segmentation.

In 2017, Konstantinos et al. used the 3-dimensional CNN approach to study the segmentation of a brain injury. In multi-channel MR imaging, it was used to detect lesions that could be traumatic brain injury or a brain tumor. It was stressed in the study that the employed procedure in Fig. 4 produced successful segmentation results.

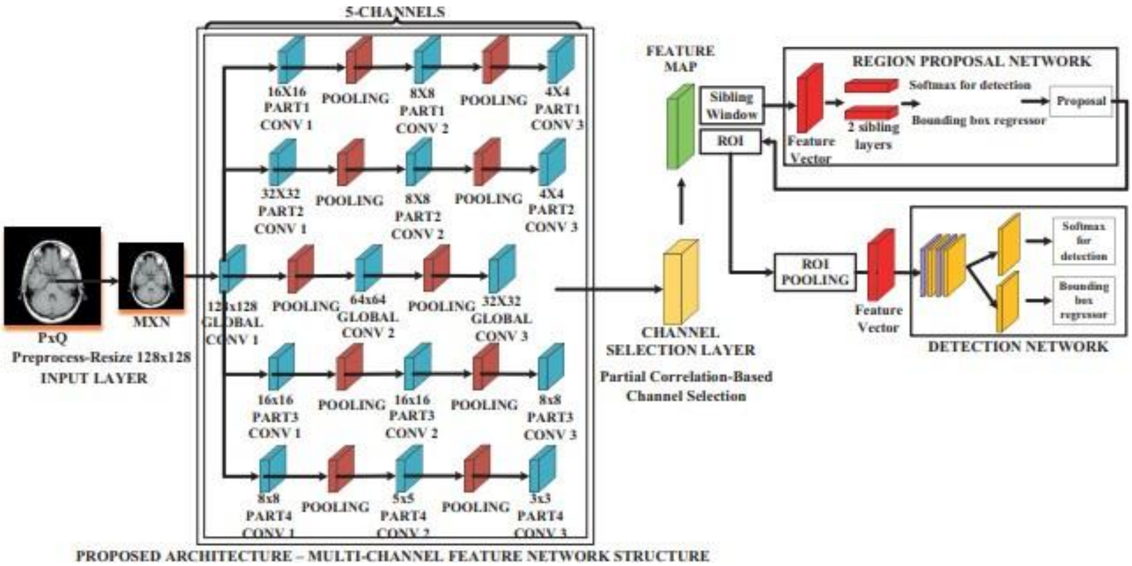

Figure 4 Block diagram of the RCNN Module

FFT in Convolutional Neural Network

The Convolutional Neural Network (CNN) was created in order to accomplish certain ground -breaking achievements and to win well-known competitions. Convolutional layers are used to generate feature maps by convolving a signal or an image with kernels. As a result, the weights of the kernels connect a unit in a feature map to the preceding layer. Back propagation is used to adjust the weights of the kernels during the training phase in order to improve certain properties of the input. CNN‘s are less prone to overfitting and are easier to train. We employ a patch-based segmentation approach, as indicated earlier in the study. CAFFE is used to build the convolutional network architecture and implement it. CNN‘s are the next step in the multi-layer Perceptron's evolution. A unit in the MLP conducts a basic calculation by adding the weighted sum of all other units it receives as input. In the preceding layer, the network is arranged into layers of units. Convolutions are the heart of CNN‘s. Sparse connections are the fundamental approach with Convolutional networks for avoiding the problem of too many parameters. In contrast to standard neural networks, each unit is not connected to every other unit in the previous layer.

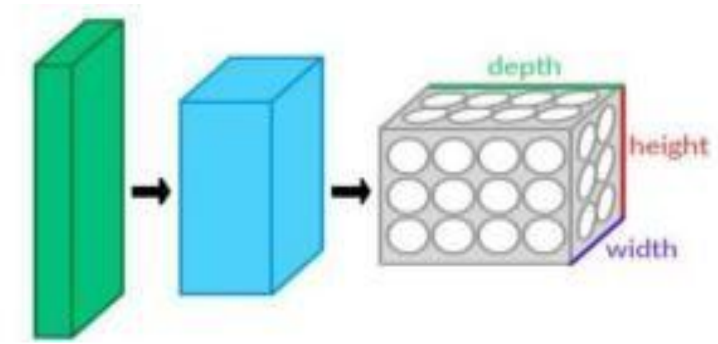

Fig 5: CNN layers arrangedin3-dimensions

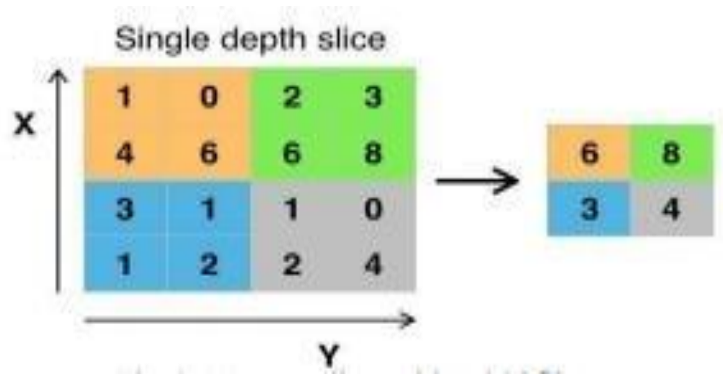

Fig 6: Max-pooling with a 2*2filter

These photos' parameters are put into a matrix and supplied to a convolutional neural network. We want to find a reliable segmentation approach, yet brain tumors have a lot of heterogeneity in intra-tumoral features, making segmentation difficult. We created a CNN and fine-tuned the intensity normalisation transformation for each tumor to reduce this complexity.

Testing phase

The segmented results are used to extract GLCM properties such as contrast, correlation, energy, homogeneity, mean, standard deviation, entropy, RMS, variance, smoothness, kurtosis, and skewness. The tumor's boundaries can be determined using the features extracted. The retrieved features are saved in a database that is used to train and test the network. Table 1 lists some of PSGIMSR's sample features.

Table 1
Feature extraction for various image sets for PSGIMSR dataset

Features	Image sample 1	Image sample 2	Image sample 3
Mean	0.005273	0.005671	0.003869
Standard Deviation	0.089659	0.089635	0.089731
Entropy	1.89451	2.16453	2.46141
RMS	0.089802	0.089802	0.089802
Variance	0.008059	0.008066	0.008065
Smoothness	0.951501	0.954745	0.935042
Kurtosis	34.5611	36.8149	20.4204
Skewness	3.12135	3.28541	1.81771
IDM	1.84505	2.95678	1.50355
Contrast	0.42436	0.432425	0.331479
Correlation	0.135197	0.099307	0.093482
Energy	0.850171	0.852803	0.789385
Homogeneity	0.955292	0.955248	0.939014

Results and Discussions

For brain tumor identification and classification, the proposed Faster R-CNN technique leverages VGG-16 as a base network. Glioma, meningioma, and pituitary tumors are represented in the chosen MR image dataset. In terms of intensity and texture, the tumor photos in a single class are not identical. Despite the fact that photos in the same class have varied appearances, the suggested faster R-CNN method can detect and categorise tumor kinds efficiently.

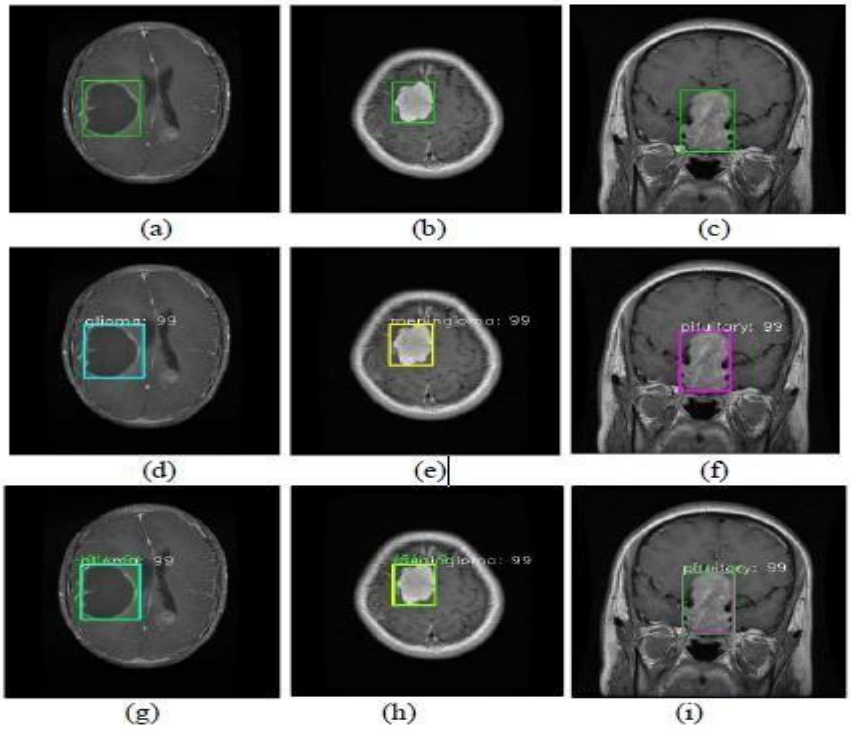

Fig. 7. The ground-truth information describing the tumor location in glioma, meningioma, and pituitary types is represented by (a), (b), and (c) in the proposed technique. For all of the aforementioned kinds, (d), (e), and (f) are the results of the suggested Faster R-CNN algorithm. The IoU calculation based on Faster R-CNN results is shown in (g), (h), and I Faster R-CNN-based multi-channel architecture was used to segment MRI images in order to determine tumor prediction. As a result, six separate deep learning network models were trained for each dataset using three different open-access MRI datasets. Performance metrics like accuracy rate, F1 score, and ROC analysis yielded more dependable and efficient outcomes when compared to previous relevant studies. In comparison to the Faster R-CNN, various architectures, the proposed model produced more effective and successful results in the study in terms of all performance assessment measures.

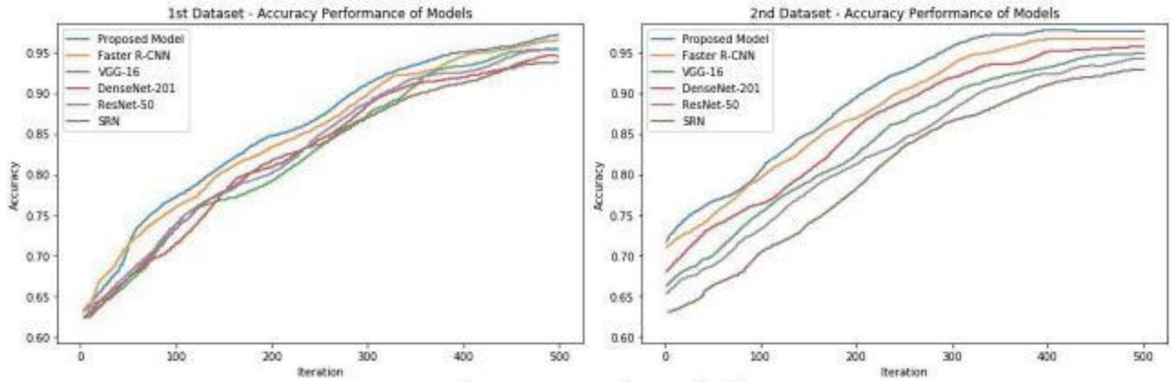

Figure 8. Accuracies & Result of applied models

Performance investigation

The trained CNN's performance in predicting samples; otherwise, the high accuracy could be attributable to a skewed dataset assignment. Because the study comprises 2990 samples, there are enough photos to be randomly divided into training, validation, and test sets with a 60:20:20 ratio, as shown in Table 8. Two hundred and nineteen photographs are randomly selected from each class's dataset and utilised for testing purposes. The activations of the CNN's convolution layers are an excellent method to view the features learned by the CNN after training. This representation is extremely useful for pixels on the input image that exhibit weakly activated channels. In the first convolutional layer, the activations of a particular channel and the strongest activation channel are shown. The channel in Fig. 6c has white pixels, indicating that it is substantially activated at tumor site. CNN has learnt that tumors are distinguishing traits that can be used to differentiate across image classes, despite never being directed to learn about tumors. These convolutional neural networks may learn relevant characteristics on their own, unlike previous artificial neural ne twork methods, which are generally manually developed particular to the application. In this work, learning to recognise tumors aids in the differentiation of a tumorous image from a non-tumorous image. Figures 9 a, b, and c show this.

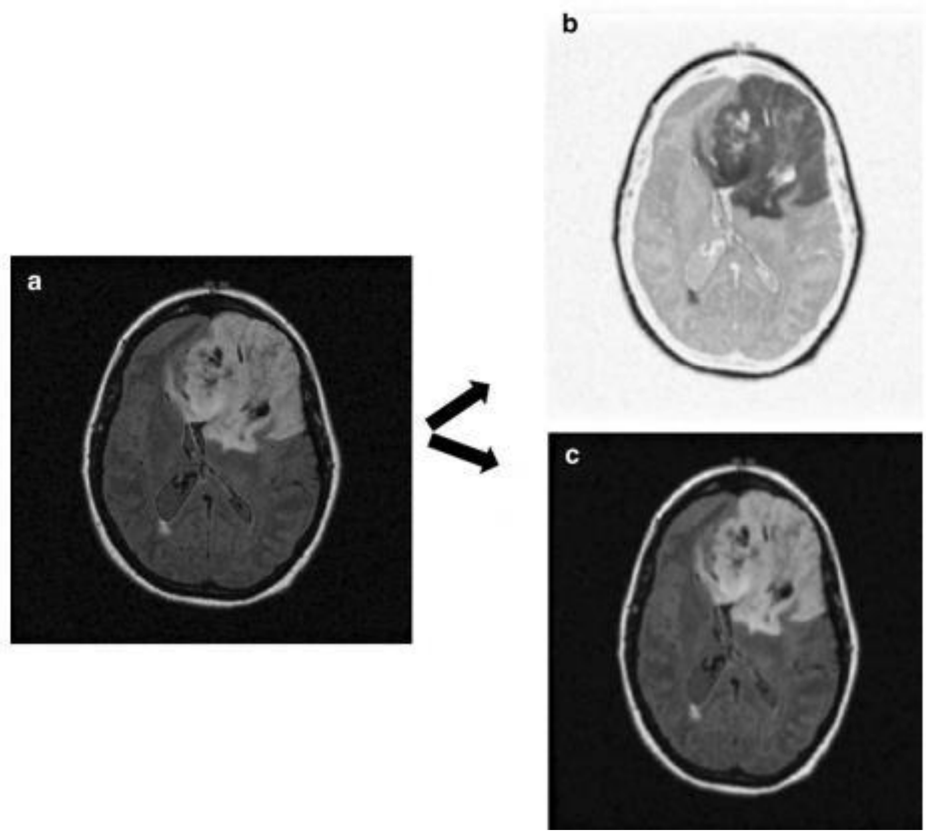

Fig. 9 a, For the Classification-1 challenge, the input picture, b activations in a particular channel, and c the strongest activation channel . Strong activations may be seen in white pixels in c, indicating that this channel is very active at tumor sites.

Conclusion

This paper proposes a unique CNN-based approach for brain tumor division in MRI images. Preparation comes first, followed by feature extraction, image segmentation, and post -processing. Various existing brain MR image segmentation algorithms were also discussed. The input MRI picture is taken, a speckle noise is applied, and then the image is pre-processed with a wiener filter. n. Mean Shift is a non- parametric clustering technique that ignores the distribution form and cluster count. As a result, when utilised to separate historical images, Mean Shift can produce superior segmentation results than model-based clustering algorithms. The retrieved attributes are utilised to categorise the input image. The image's numerous features, as well as the selection of relevant classification algorithms, are effectively utilised to improve classification accuracy. CNNs are designed to work with image data, although SVM is becoming more widely used. The creation of such a system is critical since such systems are essential for the accurate and efficient diagnosis of diseases and health conditions that are life-threatening. The accuracy of the model developed in the study was 91.3 percent, with overall precision and recall of 91 percent and 88 percent, respectively. The efficiency of the CNN models developed with the proposed optimization framework is demonstrated by the results acquired utilising the suggested CNN models and compared with state-of-the-art approaches. By selecting the best bounding box created by RPN, the proposed technique efficiently identifies brain tumor areas. Using the test dataset, a higher mAP was reached for detecting brain tumors. This technique can also be used to calculate the tumor's percentage area in relation to the brain region. This strategy can be applied to a variety of medical situations.

Data Availability

Data are available on request due to privacy or other restrictions

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