

Brain Tumor Detection Using Deep Learning

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Abstract: Brain tumors are among the most frequent and severe types of cancer, with a life expectancy of a few months in the advance stages, due to which a fast, automated, efficient and reliable technique to detect tumor is required. Various models including CT Scans, MRI and ultrasound images are used to detect tumor in different parts of body, but such methods pose difficulty in identifying and analyzing the true picture. Currently, doctors locate the position and the area of tumor by looking at the scans and images manually, which results in inaccurate detection and is often time consuming.

Deep Learning has been argued to have potential to overcome the challenges associated with detecting brain tumors in which early disease detection can be done using A.I. and Neural Network Algorithms.

In CNN a completely automated computerized system employs optimal deep features and abstraction level for testing and in VGG-16 few dropout layers are added so provide better identification. On testing the technique provides excellent and reliable results. Inception-v3 is a convolutional neural network that is 48 layers deep. ResNet-50 is a convolutional neural network that is 50 layers deep.

In our work we have used Convolutional Neural Network, VGG-16, ResNet-50 and Inception v3 to segment MRI images(JPEG) into two categories, those that have tumor and those that do not. The dataset consists of 253 images, with 155 with tumor and 98 without tumor.

Keywords: Deep Learning, Convolutional Neural Network, Artificial Intelligence, VGG-16, ResNet-50, Inception v3

Introduction: Brain tumor can be classified into cancerous and non-cancerous tumor, the cancerous tumor can quickly spread to other tissues in brain and lead to worsening the patient's condition. When most of the cells get damaged, they are replaced by new cells. If damaged cells are not eliminated with the new cells, it can cause serious consequences. The production of the new cells often results in the formation of a mass tissue, which then leads to the formation of tumor. Brain tumor detection is highly tedious and complex due to the size, shape, location and type of tumor in the brain. Identification of tumors in the early stage is strenuous as it cannot accurately measure the size, shape and location of the tumor

However, if the tumor is treated early in the formation process, the chance of patient's treatment is very high. Therefore, the treatment of tumor depends on the timely identification of the tumor. In this regard, in the field of medical imaging, AI and digital image processing has made a huge impact by using convolutional neural network (CNN). Tumor segmentation is a process of separating better and healthier tissues from the affected areas. As a result, segmentation is the most challenging task in identification techniques. Instead of being expert in the brain tumor detection, many of the modern techniques depend on general edge detection methods. Due to their efficiency in detecting features of images, deep learning algorithms are largely used for tumor segmentation tasks, they have showed significant consistency and accuracy in detecting cases

For visual identification and detection, the CNN architecture is the most popular and extensively used machine learning approach. In this project, we use a convolutional neural network (CNN) technique combined with Data Augmentation and Image Processing to analyses MRI images(JPEG) to determine which images have and which do not have brain tumors. Medical image segmentation takes a long time other medical experts. Hence, precisely identifying a brain tumor manually is next to impossible task also one can find that there is a lot of difference among doctors opinion. To overcome these constraints, computer assisted technology is the need of the hour, as the medical field requires quick and reliable procedures to identify life threatening diseases such as cancer, which is the top cause of death for patients worldwide. Hence, utilizing

Brain MRI Images(JPEG), we present a method for classifying MRI images(JPEG) into those with and without the presence of a brain tumors utilizing a data augmentation strategy and a convolutional neural network model in our study.

Proposed System: Edge detection is a process of finding and examining certain disruptions in an image. The disruptions are sudden changes in the information stored in image which identifies boundaries of objects in a scene. Currently, there are many edge detection techniques available which are used to identify specific types of edges. The aim is to reduce the information stored in the image while conserving the required properties

Efficient edge detection mechanism is used in the project



Fig.1 Edge detection

We propose a method that is sequential in its operation. It uses techniques such as convolutional neural network, max pooling, flattening and a dropout layer to avoid over-fitting. We use transfer learning to assign weights to our features. The MRI image(JPEG) sequentially goes through the above stated layers and feature extraction is performed. DICOM images are large in size when we use them to train a model, so to decrease the parameter size we use DICOM converted JPEG images from Kaggle. The MRI images(JPEG) have been divided into training and testing parts where the first part is used for further training of a VGG-16 CNN, ResNet-50, Inception v3.

The algorithm demonstrates the step-by-step working process of the proposed system.

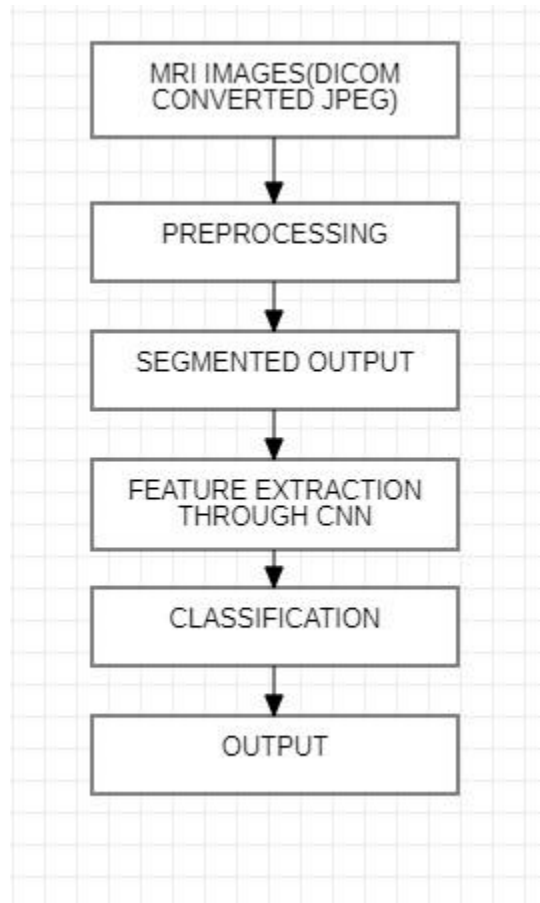


Fig. 2 Flowchart

Literature Review: The lump in the brain tumor can be present at different locations and shapes, during the time of segmentation. Brain tumors are segmented using the MRF system. Generative models successfully generalize hidden data with some constraints in the training step. Without the use of a specific model, these strategies can be employed to comprehend the pattern of a brain tumor. The distribution of identical and independent voxels on the ground of context factors is constantly taken into account in these styles. As a result, some small or isolated clusters of voxels may be distributed incorrectly into the wrong class, generally in anatomically and physiologically incongruent places. To avoid these issues, numerous experimenters used probabilistic predictions to fit neighborhood information into a Conditional Random Field (CRF) classifier. Deep CNN models are used to automatically learn scales of complex data attributes.

In this work we have enforced a pre-trained and advanced interpretation of VGG-16 Convolutional Neural Network (CNN) to categorize brain tumor images taken with camera into two types that is cancerous and normal images. Although the network model does not need feature extraction to apply a small quantum, training CNN architecture is tough and tedious since it needs a dataset for testing and training before the structure is ready for classification, which is not always available. In addition, hardware is required for computing the massive factor for large images. Since DL Algorithms can effectively express critical relations without demanding a wide variety of equipment, they are a remarkable development in ML. As a result, they evolved fleetly to serve as a blessing in several health informatics fields, such as informatics, healthcare analytics, and pattern identification.

Methodology Result and Discussion: The dataset used in the design is Brain MRI Images(JPEG) for Brain Tumor Identification, which is easily available on Kaggle. The dataset includes 253 images of brain MRI, out of which 155 have tumour and 98 images do not have tumour. Our dataset was divided into three parts for training, validation, and testing. The

training data is used to learn the model and get used to the features, while the validation data is used to estimate the model and interpret its parameters.

The validation is implemented using Cross-Validation. Our model’s final evaluation will be on the ground of test data.

In some cases, the areas of fat in the images are incorrectly identified as tumor, or the tumors may not be seen by the doctor; the most exact treatment is completely depended on the doctor’s skill. In this paper, the CNN has been used for Brain tumor detection using some images. There were some margins of the images gathered from the imaging centers, which were removed to provide a high resolution view of the image. One of the main reasons for using the feature extraction technique was to increase the accuracy of the network.

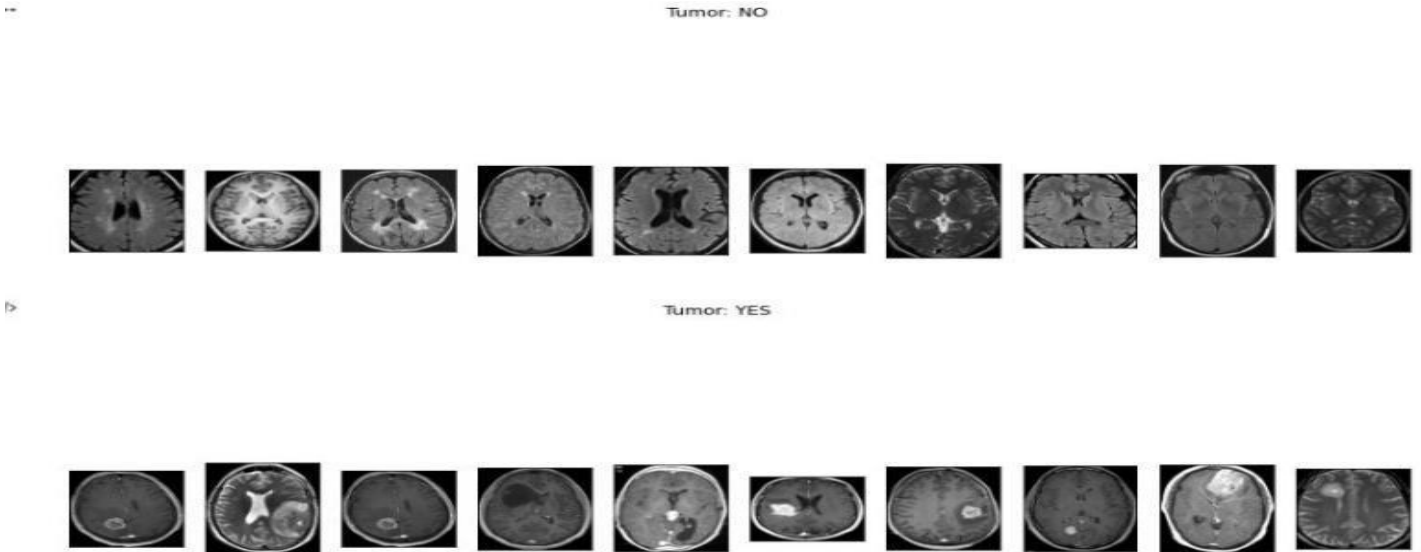
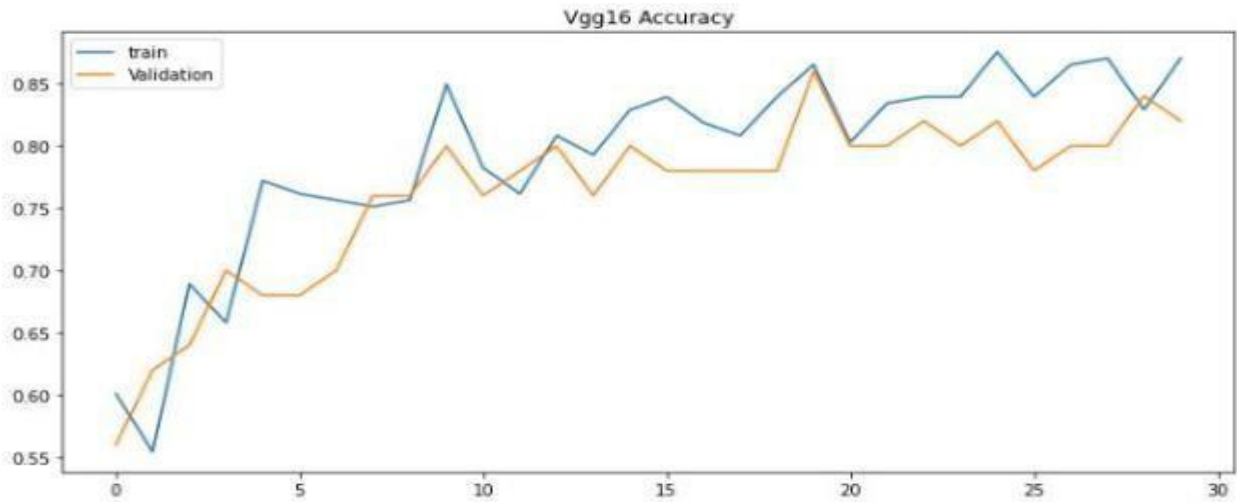
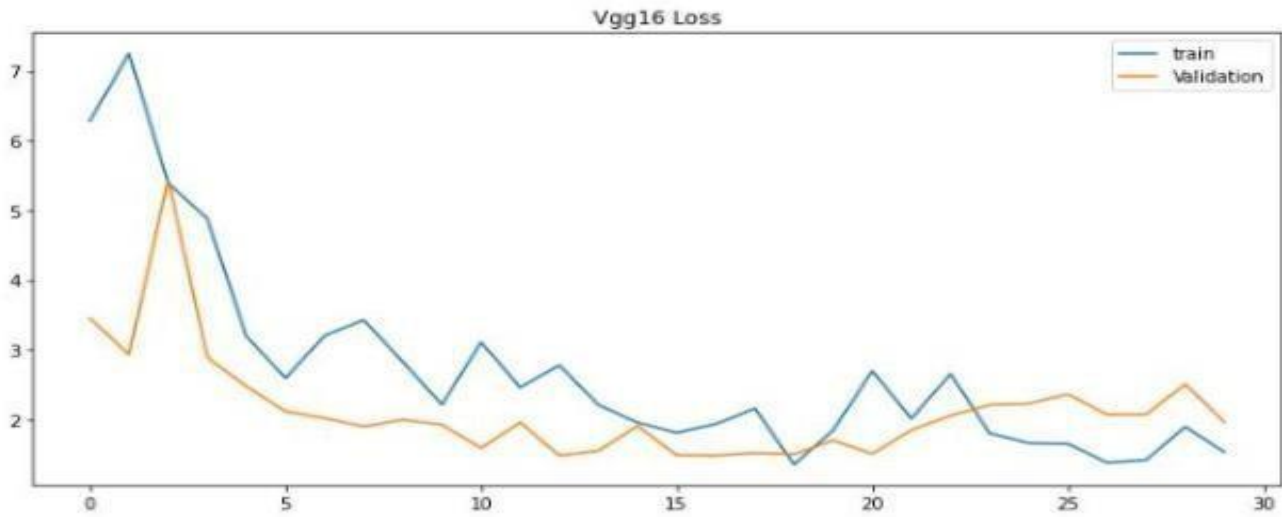


Fig. 3 Data Set

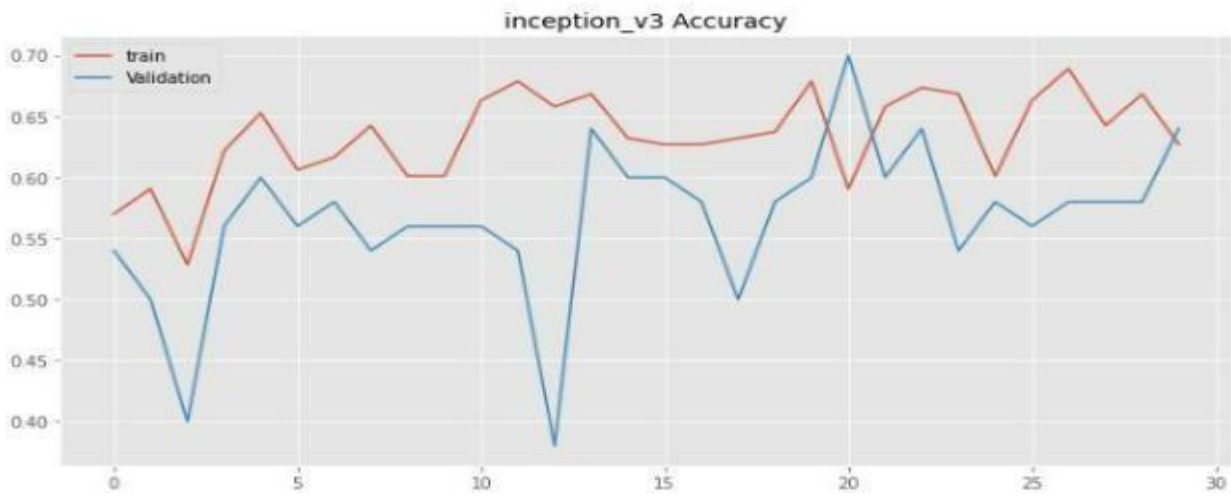
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*** Model: "sequential"
-----
Layer (type)                Output Shape                Param #
-----
vgg16 (Functional)          (None, 7, 7, 512)          14714688
dropout (Dropout)           (None, 7, 7, 512)          0
flatten (Flatten)           (None, 25088)              0
dropout_1 (Dropout)         (None, 25088)              0
dense (Dense)               (None, 1)                  25089
-----
Total params: 14,739,777
Trainable params: 25,089
Non-trainable params: 14,714,688
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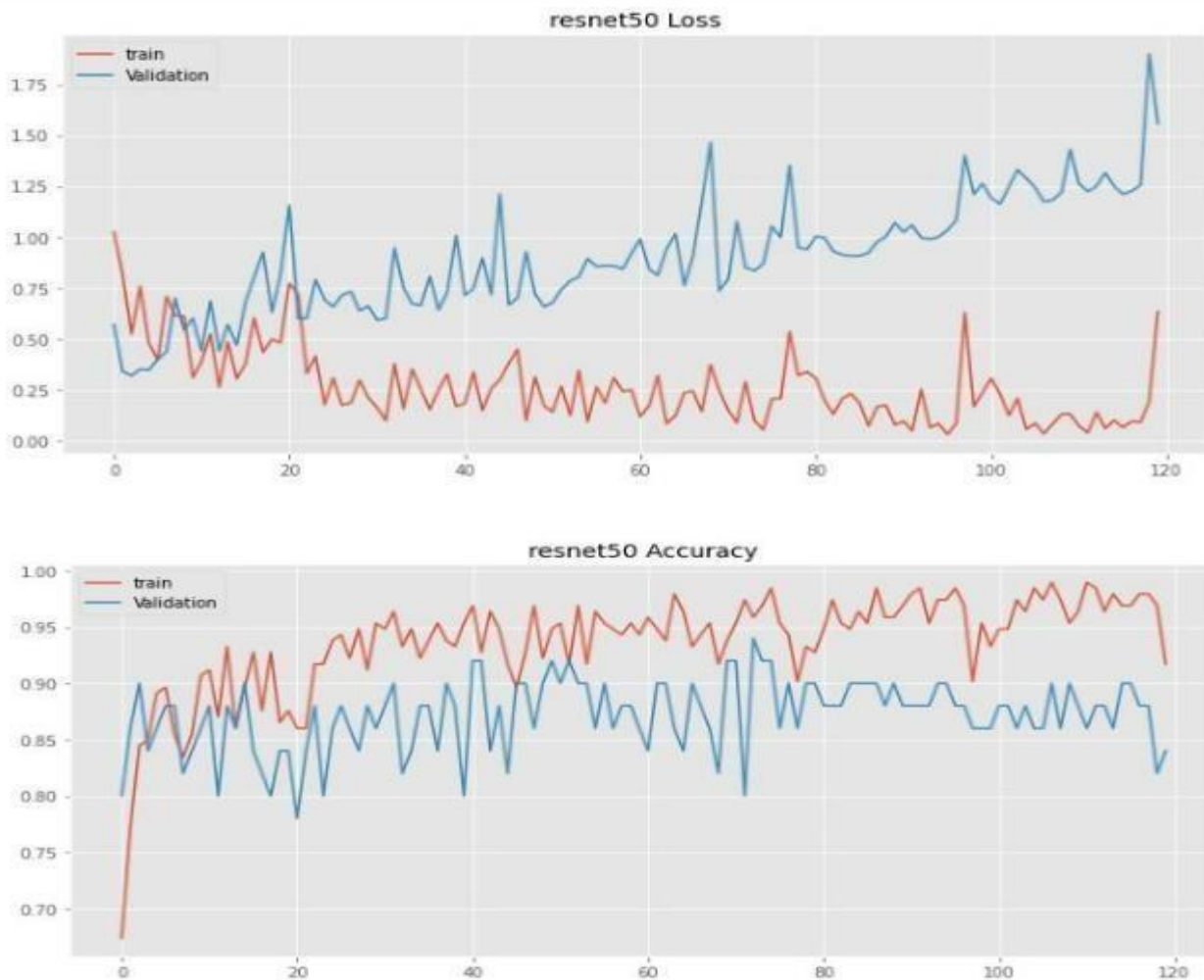


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*** Model: "sequential_2"
-----
Layer (type)                Output Shape              Param #
-----
inception_v3 (Functional)   (None, 5, 5, 2048)       21802784
dropout_4 (Dropout)         (None, 5, 5, 2048)       0
flatten_2 (Flatten)         (None, 51200)            0
dropout_5 (Dropout)         (None, 51200)            0
dense_2 (Dense)             (None, 1)                51201
-----
Total params: 21,853,985
Trainable params: 51,201
Non-trainable params: 21,802,784
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```



Layer (type)	Output Shape	Param #
resnet50 (Functional)	(None, 7, 7, 2048)	23587712
dropout_10 (Dropout)	(None, 7, 7, 2048)	0
flatten_5 (Flatten)	(None, 100352)	0
dropout_11 (Dropout)	(None, 100352)	0
dense_5 (Dense)	(None, 1)	100353

Total params: 23,688,065
 Trainable params: 100,353
 Non-trainable params: 23,587,712



Images were reshaped into 244×244 size and passed through a convolutional layer with three filters. Subsequently, the output passes through maxpool and flattening layers. The model has been trained with 30,120 epochs.

The essential variables stated for the given model showed that it was effective in finding original tumor areas, while avoiding false ones. Most current techniques focus on the entire tumor region, resulting in incorrect measurements for core and augment regions. The methods proposed in the document should include statistical and deep learningbased technology, with CNN dealing with task complexity. Due to the clinical significance of the tumor detection problem, time constraints, sensitivity, and accuracy are essential. The results validated the efficiency and efficacy of the proposed models, especially in terms of fundamental and augmenting regions of some values, where it outperformed previous methods by a wide margin.

MODEL	ACCURACY	PRECISION	RECALL	F1 SCORE
CNN	50%	50%	100%	66.7%
Inception v3	60%	57.1%	80%	66.7%
ResNet-50	90%	100%	80%	88.9%
VGG-16	90%	100%	80%	88.9%

Fig. 4 Result Table

Conclusion and Future Scope: In this project, we used MRI images(JPEG) of the brain to divide into two types, one having tumor and the other not having tumor. We executed a sequential model where the images were reshaped to 244 x 244 then the convolutional layer, max-pooling layer, flattening is performed on those images to convert it to a vector form. Hence, we used ImageNet dataset which contains a large number of medical pictures, which helps in feature enhancement. The architecture used is VGG-16, ResNet-50, Inception v3 which is further improved by using a dropout layer. When compared to manual detection done by doctors or clinical physicians, the results of the experiments on different pictures show that the analysis for brain tumour detection is quick and efficient. Our research show that the described way can help in the accurate and timely detection of brain tumours, as well as it can locate the exact region of tumor. As a result, the given method is essential for identifying tumours from images. According to our research, the given method is essential for taking the correct decision by medical experts

The given method can be expanded for better classification in future research. These methods can efficiently treat other types of tumors and disorders. This model can be used during operations for searching and locating the exact region of tumor. Detecting tumours in the operation theatre could be done in real time situations. Future research can make use of methods to acquire the nearest location of infected area in the brain to isolate them from unaffected parts, testing the efficiency of neural network, improved models could be done in the near future.

References:

- [1] Nilesh Bhaskarrao Bahadure, Arun Kumar Ray, and Har Pal Thethi, "Image Analysis for MRI Based Brain Tumor Detection and Feature Extraction Using Biologically Inspired BWT and SVM", 2017
- [2] Luxit Kapoor, Sanjeev Thakur "A Survey on Brain Tumor Detection Using Image Processing Techniques", 2017
- [3] Praveen Gamage "Identification of Brain Tumor using Image Processing Techniques",2017
- [4] Deepa, Akansha Singh "Review of Brain Tumor Detection from MRI Images", 2016
- [5] Devendra Somwanshi , Ashutosh Kumar, Pratima Sharma, Deepika Joshi "An efficient Brain Tumor Detection from MRI Images using Entropy Measures ", 2016
- [6] A. Demirhan, M. Toru, and I. Guler, "Segmentation of tumor and edema along with healthy tissues of brain using wavelets and neural networks", 2015
- [7] Yaqub, M.; Feng, J.; Zia, M.S.; Arshid, K.; Jia, K.; Rehman, Z.U.; Mehmood, A. "State-of-the-art CNN optimizer for brain tumor segmentation in magnetic resonance images", 2020
- [8] Amin, J.; Sharif, M.; Yasmin, M.; Fernandes, S.L. "A distinctive approach in brain tumor detection and classification using M.R.I. Pattern Recognit. Lett.", 2020