BRAIN TUMOR DETECTION AND CLASSIFICATION

Abhishek Kadu[1], Pragya Khandelwal[2], Shrija Keshari[3], Dhiraj Bhise[4*]

[*]abhishek.kadu37@nmims.edu.in[1], pragya.khandelwal42@nmims.edu.in[2], shrija.keshari41@nmims.edu.in[3], dhiraj.bhise@nmims.edu[4]

Information Technology, Final Year Student, SVKM's NMIMS MPSTME, Shirpur, India[1,2,3], Assistant Professor, Information Technology, SVKM's NMIMS MPSTME, Shirpur, India[4]

Abstract

A brain tumour is a collection of tissue that has been pre arranged by the gradual addition of abnormal cells. It happens when cells in the brain shape irregular formations. It has recently become a leading cause of death for many people. Since brain tumours are among the most dangerous of all cancers, prompt diagnosis and treatment are needed to save a life. Because of the development of tumour cells, detecting these cells is a challenging task. It is critical to equate the treatment of a brain tumour with that of an MRI. There are three types of brain tumours namely Glioma,Pituitary,Meningioma.Neural Network is used to classify the tumor.Basically MRI images of different type of tumor is given as input to the system on which the system is trained and input images are taken to test the model. One of the most important things for a doctor to do before starting treatment is to detect a tumour. Traditionally, tumours were discovered by drilling a hole in the skull and removing a small part of the tumour to inspect. [2]Detection has become easier with the help of machine learning and MRI images. The system is given MRI images of patients, and it performs detection and classification on the given set of images. There are numerous algorithms available for this task. In this paper, some techniques for detecting and classifying brain tumours are discussed. Our system accepts brain MRI images as input.The main goal is to provide doctors with a high[2] - precision system for classifying tumour types.Feature extraction by using the Keras and Sequential model is used as we would be having only one input image and the output would be given so we preferred using Sequential Model. CNN is used to classify brain tumours into stages automatically. The brain tumour spread area is detected as well as segmented using the K-means clustering algorithm.. Numbers of defect cells are found in the spreaded region. This paper concentrates on detecting and classifying the types of tumor if no tumor is detected it is given as output to the user as no tumor was detected and if tumor is detected the user would get an output displaying the type of tumor along with the images.[4] The main goal is to provide doctors with a high - precision system for classifying tumour types.

Keywords: Deep learning, Brain tumor, Magnetic Resonance Images (MRI), Feature Extraction, Segmentation, Classification, Mask R-CNN, Glioma, Pituitary, Meningioma.

1 Introduction

Today cancer is one of the leading causes of death. According to World Health Organization (WHO) In 2018 9.6 million people worldwide have died of cancer. With early detection, half of these could have been prevented.[8]Brain tumour is one of the most dangerous types of cancer it is estimated that around 17,760 people are predicted to die from brain tumours in the year 2019.[9]

The symptoms of a brain tumour vary depending on the size, type, and location of the tumour. Because of its invasive nature and limited space a brain tumour is extremely dangerous and life-threatening. A brain tumour is a collection of abnormal cells that grow inside or around the brain. [11]Tumors can kill all healthy brain cells directly, and they can also harm healthy cells indirectly by crowding other parts of the brain. The human brain's complex structure makes diagnosing a tumour in the brain region difficult. For tumour diagnosis MRI is a useful method for obtaining high-quality brain image and is widely used.

Image processing is the process of analysing and manipulating a digital image, with the goal of improving its quality. This method transforms an image into a digital format in order to extract or enhance it.MR images can be used to extract detailed information about human anatomy and tissues. [18]MR images are primarily used in biomedicine to detect and visualise finer details in the body's internal structure. Magnetic resonance imaging generates a single signal that can be detected and is spatially enclosed, resulting in images of the body.Brain tumour detection can be thought of as an image segmentation problem in which the tumour is labelled on the image. MRI images have been subjected to various image processing methods as well as machine learning algorithms in order to solve this problem.

According to the American Brain Tumor Association and WHO, the most popular classification scheme uses a tumour scale of grades I and II to be benign, and grades III and IV are malignant tumours.[24]

Segmentation is used in medical imaging modalities to detect infected tumour tissues. [4?]In image analysis, it is a essential and important step to divide an image into different regions or blocks that share similar and equal properties, such as colour , texture, contrast, brightness, boundaries and grey level.

For diagnosis, multiple magnetic resonance imaging (MRI) sequence images are used in science. For better treatment, the early detection of a brain tumour is a critical issue. When a brain tumour is clinically suspected, it is important to carry out a radiological test to determine its location, size and impact on the surrounding areas.[19]

Deep learning is a machine learning technique that makes use of a neural network architecture with hundreds of hidden layers between the input and output layers. It's been used to solve a variety of problems, including image classification, object detection, and speech recognition.

Convolutional neural networks (CNN) are a category of deep learning architecture that performs one of three operations: convolution, pooling, or rectified linear unit (ReLU).

A regular CNN can determine whether or not an image contains an object, but it cannot determine its position.Region-based CNN (RCNN), on the other hand, is specifically used for finding objects in photos and is an expanded variant of CNN.Automatic segmentation of large volumes of MRI images has been successfully achieved using deep learning techniques. By distinguishing distinct characteristics, CNN-based algorithms for automatic MRI segmentation for brain tumors achieved successful results.[17]CNN architecture that takes local and contextual knowledge into account as one is the more recent solutions to this issue.Pre-processing step normalises the images, and a post-processing step removes false positives, according to their procedure. In this analysis, Mask R-CNN approach is used to analyse MRI brain images in order to identify and find tumours.[19]

All coding is performed in the Python programming language (version 3.6.6), and the deep learning algorithm is introduced using the TensorFlow library. We came across some dataset during the research for this model but some have not fulfilled our requirements,other had RGB images but we were concerned of using MRI images as they gave accurate output and performing feature extractions is comparatively easier on these images.We got out dataset from Kaggle which was available for research.

Our designed model work work in the following manner:- MRI images of different types of tumor would be given as input and the model would be trained for the said images and then feature extraction would be performed in order to remove noise from images .In our work we have trained our model on three types of tumor Glioma,Pituitary,Meningioma.In our work we have used CNN and Relu as activation function.Later we have used Dropout to prevent overfitting ,batch normalization to normalize input heading into the next layer and to ensure the network always create activation with the same distribution.We have also used MAxPolling so that system can learn robust pattern and then we used dropout and batch normalization.

2 Literature Review

Many Brain tumor classification models are deployed in the past few years.We have reviewed some of the papers and their summary along with the methods used are given below. Xiao et al [1] suggested a method for estimating features based on the relationship between brain lateral ventricular (LaV)[26] deformation and tumour. Pre-processing, feature extraction, segmentation, and classification are the four phases of the proposed technique.The problem of strength non-standardization, geometric non-uniformity, and redundant data in the background image and skull are discussed in the first step. For feature extraction, lateral ventricular deformation was used.Unsupervised segmentation methods are used in the segmentation section. The most commonly used methods in this paper are K nearest neighbours (KNN) and traditional Fuzzy connected C-mean (FCM)[24]

Nandagopal and Rajamony [2] They presented a two-level discrete wavelet transform that yielded a combination of wavelet statistical features and wavelet co-occurrence texture function . For brain tumour segmentation, a combination of WST and WCT is used, and for feature extraction of tumour area derived from two stage discrete wavelet transform, a combination of WST and WCT is used. The best texture features are chosen using a genetic algorithm from the collection of extracted features. The proposed method has a classification accuracy of 97.5 percent.[26]

Kalbhani et al [3] They developed a system for classifying MR images into normal and abnormal in their paper. At the first two levels, the input image is transformed into a two-dimensional discrete wavelet transform (2D DWT), and the wavelet coefficients of the details subband are modelled using the Generalized Auto Regressive Conditional Hetroscedasticity (GARCH) statistical model.[28]Principal component analysis (PCA) and Linear Discriminant Analysis (LDA) are used to extract the proper function and minimise redundancy from the primary feature vectors after feature vector normalisation.

Finally, the extracted features are added separately to the K nearest neighbour (KNN) and support vector machine (SVM) [24]classifiers to decide whether the images are regular or abnormal.

Sindhu mol et al [26]is centred on spectral angle based feature extraction and spectral clustering independent component analysis, proposed a method to improve the classification of brain tumours from magnetic resonance images (SC-ICA). Spectral distance dependent clustering is used to separate the MR image into different clusters. Along with SVM, independent component analysis (ICA) is performed on the clustered results.For this study, T1weighted, T2weighted, and proton density fluid inversion recovery images were used. To determine the stability and efficiency of SC-ICA based classification, a comparison is made with ICA based SVM and other traditional classifiers.

Navarro et al[25], worked on different HMRS modalities, such as long and short echo periods, and an ad hoc combination of both, they introduced a new method for feature selection of dimensionality reduction and several off-the-shelf classifiers in their paper. They use an entropy selection algorithm for feature selection, which is a simple way to produce a relevant subset of spectral frequencyIn the boot strap samples, feature selection is performed independently in the classifier. Then, using the previously selected set of features, a set of classifiers is built on the boot strap samples, with the result being the selection of a particular classifier for each data form.

Georgiadis et al[20] On MRI, a software device was used to distinguish between metastatic and primary brain tumours. The research used a Modified Probabilistic Neural Network (PNN) classifier with a nonlinear least square feature transformation (LSFT).The Tl weighted image is used to remove six elements. They achieved a classification accuracy of 95.24 percent for distinguishing between metastatic and primary tumours and 93.48 percent for distinguishing gliomas from meningiomas in the first level, and 100 percent in the second level. choosing the ROI for the entire pixel

Lin et al [22] They present a system for precise, reliable, and effective quantification of brain tumours using MR imaging in their paper. The aim of this project is to create a computerised system and assess its efficacy in routine clinical practise. The image (FLAIR, TI, and T2) is processed separately in this system.

The steps are as follows:

- For each protocol, an MRI image is first standardised, and then the procedure is performed on the standardised image.
- The fuzzy connectedness algorithm is used to segment the FLAIR images.
- The FLAIR images are segmented to compute the edoema volume.
- A separate picture is obtained [14]by registering the TI and TIE images.
- The representation of the difference is segmented.
- All segments region volume are compared.

3 Introduction to Mask RCNN

The model is split into two sections: To suggest candidate object bounding frames, an area proposal network (RPN) is used. To create a mask for each class, a binary mask classifier is used.[11]

The Mask RCNN is a deep neural network designed to solve the issue of instance segmentation in machine learning and computer vision. To put it another way, it can distinguish between various objects in a picture or video. It takes an image and returns the object's bounding frames, classes, and masks.Mask RCNN is divided into two levels. First, it provides suggestions dependent on the input picture for regions where an object may be present. Second, based on the first stage proposal, it estimates the object's type, refines the bounding box, and produces a mask at the pixel level of the object. The backbone structure is related to both points.[14] Backbone is a deep neural network in the FPN style.

A bottom-up pathway, a top-bottom pathway, and lateral connections make up this system. [17]Any ConvNet, typically ResNet or VGG, that extracts features from raw images can be used as a bottom-up pathway. The feature pyramid map generated by the top-bottom pathway is comparable in size to the feature pyramid map generated by the bottom-up pathway.

Figure 1

1. In the first part what basically happens is that an RPN which is a light-weight neural network scans the entire FPN top-bottom pathway and suggests regions that may contain artefacts. That's what there is to it. Though scanning the feature map is a time-saving process, we also need a way to link features to their raw image locations.Anchors are a group of boxes that have predetermined positions and scales in relation to photos.[24] Person anchors are allocated ground-truth classes (only object or context binary classified at this time) and bounding boxes based on some IoU value.Since various scale anchors attach to different levels of the feature map, RPN uses these anchors to determine where on the feature map an object should be placed and the size of its bounding box[15, 19].

2. At the second stage another neural network takes the first stage's suggested regions and assigns them to multiple separate areas of a function map level, scans these areas, and creates object types, bounding boxes, and masks[2].
   The technique resembles RPN in appearance. Step two differs in that it uses a technique called ROI Align to find the appropriate areas of the feature map without the use of anchors, and there is a branch that generates masks for each object at the pixel level.[4]

4 PROPOSED METHOD

4.1 Dataset Gathering

There are many different ways for data gathering it can be done either by collecting MRI images from web or by creating a completely new dataset by gathering images from an hospital.However the second method is costlier.[13] The proposed method is tested on publicly accessible datasets the Brain Tumor Kaggle (BTK) Dataset, which differ in structural sophistication, acquisition angle, instruments, noise, and bias field-effect, among other things. [15]The BTF dataset comprises approximately 3000 actual MRI images.The images are in JPEG format and are in grayscale.

4.2 Training

For training and testing the Mask R-CNN, the tumor locations in all the images is labelled and saved in an file. The model is trained at an epochs 20 and around thousand images of each types are tumor are taken for training. For this purpose, different images are saved in different files.Four different files are created namely No Tumor,Glioma,Pituitary and Meningioma for training and for testing randomly brain MRI images are taken from the web are given as input and the result in generated.We kept and epoch of 30 and an batch size of 32. [7]

Below are the images from our dataset which basically represent four different types of images and each folder contains around thousand images.The trained images are saved into numpy arrays.

The graph below explains the training of our model as we can see that the Test axis in exponentially[8, 9] decreasing and the validation is increasing from which we can conclude that the model is trained perfectly if the validation would have decreased and the test would have increased

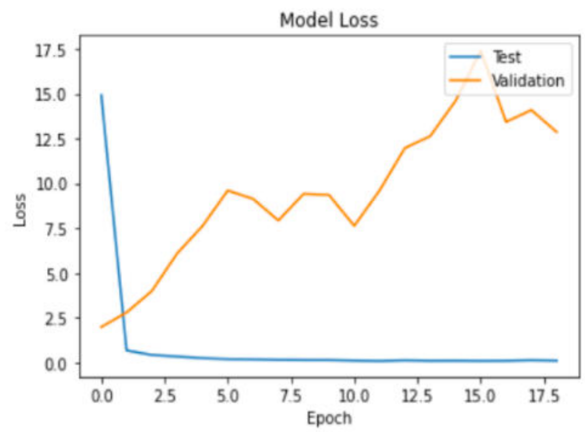


Figure 2: Graph

We would have known that the model is overfitted and if vise vera would have happened we would have said the model is underfitted.

4.3 Preprocessing

The only goal of Brain Tumor Identification and Classification is the ability to use machine learning to identify and recognise the type of brain tumour. [16]Certain objects, such as noise, bias area, or strength in-homogeneity, are frequently present in MRI images generated by various MRI machines and must be corrected in order to improve segmentation performance. In our paper we have used a total of 32 filters

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 148, 148, 32)      896
_________________________________________________________________
activation (Activation)      (None, 148, 148, 32)      0
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 74, 74, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 72, 72, 32)        9248
_________________________________________________________________
activation_1 (Activation)    (None, 72, 72, 32)        0
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 36, 36, 32)        0
_________________________________________________________________
flatten (Flatten)            (None, 41472)             0
_________________________________________________________________
dense (Dense)                (None, 32)                1327136
_________________________________________________________________
activation_2 (Activation)    (None, 32)                0
_________________________________________________________________
dropout (Dropout)            (None, 32)                0
_________________________________________________________________
dense_1 (Dense)              (None, 4)                 132
_________________________________________________________________
activation_3 (Activation)    (None, 4)                 0
=================================================================
Total params: 1,337,412
Trainable params: 1,337,412
Non-trainable params: 0
```

Figure 3

and used max pooling to reduce the spatial dimensions of the output volume and an input shape of images of dimension[150,150,3] is taken. [24]Max Polling generally done to help over-fitting by providing an abstracted form of the representation.We are also using flatten which has input size(2,2) and will give an output of 4 and dense with an output of 32.

4.4 Tumor localization and segmentation

Mask RCNN is used to localise and segment tumours. Our objective for segmentation is to automatically identify and segment the brain tumour against a complex backdrop without the need for human involvement. Using the Mask RCNN, we hope to predict tumour or non-tumor regions in the given MRI pictures[6, 11].Steps involved are:-

- Feature extraction
- Region proposal network (RPN)
- Region of interest (ROI) classifier and Bounding box regressor (BBR)

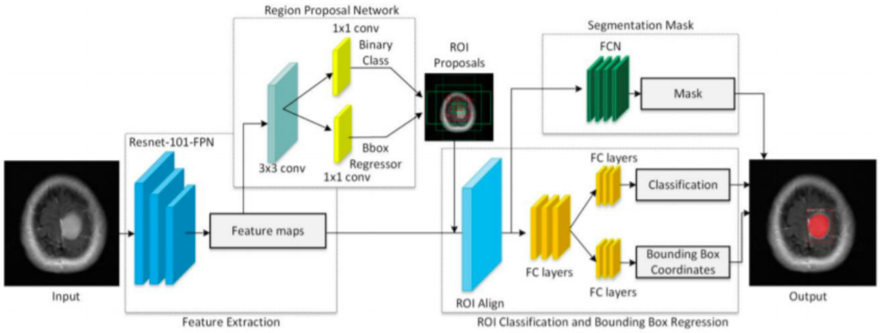


Figure 4: Tumor localization and segmentation

4.4.1 Feature extraction

To extract relevant features from the input image, the backbone network is used. To remove stable functionality, we considered ResNet101.Resnet 101 boosts accuracy as well as processing speed. Corners and edges are extracted at the most simplistic level, while texture and colour are extracted at the advanced level.The feature map generated as result is improved using FPN.Below is the diagram depicting our model.[18]

4.5 Preprocessing

4.5.1 Region proposal network (RPN)

The RPN network generates ROIs using the function map computed in the previous stage.[16] A 33 percent of convolutional layer is used to scan the image with a sliding window in order to produce relevant anchors that form the bounding box in various sizes and are spread throughout the entire image.The BBR builds bounding boxes based on the Intersection-over-Union (IoU) value you assign. If an anchor's IoU with a ground-truth (GT) box is greater than 0.7, it is graded as a positive anchor (FG class), otherwise negative.Since the RPN will generate regions with a lot of overlap, the non-maximum suppression algorithm is used to hold the regions with the highest foreground score and discard the others. The resulting field of concern is then carried on to the next level for classification.[18]

4.5.2 Region of interest (ROI) classifier and Bounding box regressor (BBR)

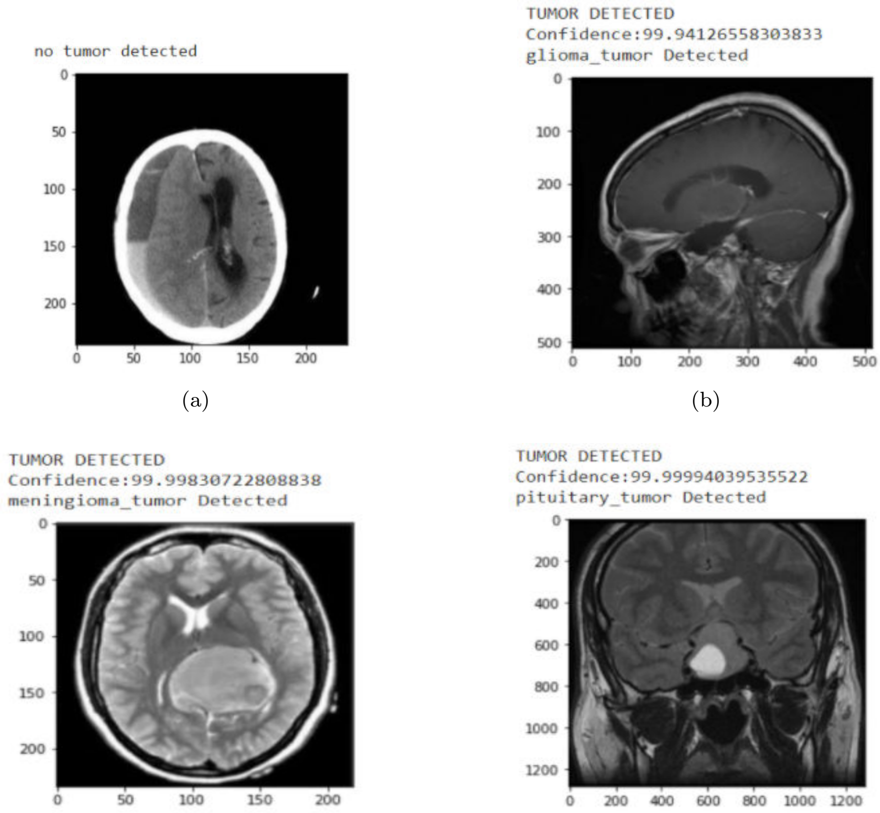
The proposed ROI and function map are fed into this network.Unlike the RPN, this network is more complex and categorises data.ROIs for a certain type, such as tumours and non-tumors, and more increases the bounding box's height.[5]The aim of the BBR is to fine-tune the position and scale of the bounding box so that it perfectly encloses the tumour area. Since the feature map is down-sampled k times from the original image scale, the ROI boundaries seldom match the granularity of the feature map.The ROIAlign layer is used to extract fixed-length feature vectors for arbitrary-size candidate regions in order to resize the feature maps. The ROIAlign layer uses bi-linear interpolation to prevent the misalignment problems that may occur by using the quantization operation in the ROI pooling layer.[9]

4.6 Classification

Classification is done to identify the tumor class present in the image.It is an system which separates all pixels in a digital image into categories. It is used to distinguish brain tumours on MR images into three categories normal, Glioma,Meningioma,pituitary. [11]The proportion of correct classifications is the correct classification rate.The claddief images is given as output along with the accuracy and the image.The predict() method is used of Numpy which accepts a NumPy array of one or more lists where each list is regarded as a sample.The images saved in numpy array during training are used to compare with the input images.[13]

5 Results

We have achieved an accuracy of 96 percent in our model,Brain MRI images dataset from Kaggle [17]for training and used it to train our model.We have used various kinds of filters to add to our feature and get accurate features to be added to our Model.



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(a) (b)

(c) (d)

Figure 5: Output

We used Mask R CNN with ResNet-101 to apply the algorithm. We used pre-trained weights from the COCO dataset to configure the model and used transfer learning to fine-tune the model on MRI datasets for tumour segmentation.[4]

Our model uses MRI images as input and provides an accurate output which can be operated on a standard laptop.Below are the output our system has generated on some of the tested images.

6 Conclusions

We present a model for the detailed segmentation of brain tumours from MRI images in this article. We have achieved and accuracy of 96 percentage in our findings.

We were able to detect tumor and also to classify three types of tumor namely Glioma, Pituitary, Meningioma.[19] We suggest using MRI images over RGB images as they are easier to handle and provide accurate results.

The findings show that the suggested procedure accurately delineates the tumour area and can be used as an automatic diagnostic tool.[15] We want to continue our research by classifying various types of brain tumours.

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