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Brain Tumor Detection using Deep Learning Technique (CNN Model)

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Abstract

There are different modalities used for scanning human body parts. MRI (Magnetic Resonance Imaging) is one of the important techniques among all modalities for scanning human brain as it has much information compared to other modalities such as X-ray, PTE, CT scan, etc. Many researchers are using MRI scanning for detection of abnormalities in human brain. In this project, automatic detection of brain tumor is proposed using deep learning technique. There are many existing works on detection and classification of brain tumor from different modalities, but the existing technique is having less accuracy and more time complexity. To overcome drawback of existing technique, proposed technique based on deep learning technique as CNN (Convolutional Neural Network) model is implemented. Proposed CNN model is analyzed by both subjective and objective way. Proposed technique has low run time complexity and higher accuracy compared to state of art techniques.

Keywords: MRI scan, brain abnormalities, Deep learning, Convolutional Neural Network, accuracy.

I. Introduction

Medical imaging is one of the important topics in research field which leads to smart hospitality and helps to overcome the drawbacks of existing manual techniques. Detection of abnormalities from brain also helps to overcome manual mistakes done by experts and give them intelligent solution even in complex pathologies. MRI scan has much information regarding brain which helps to find abnormality automatically using different computer vision based segmentation techniques.

Many people worldwide effected by the Brain Tumor. It also detected in the early age, not only limited with the old age people. Functioning of the brain is limited inside the brain cranium by brain tumor. Brain Tumor is the abnormal growth of cell. With the advancement of image processing (IP) and machine learning (ML), early detection of the brain tumor is possible. By studying several research papers, overview of the analogous papers is quoted and stages of image processing are discussed in this paper. To predict brain tumor gist of technologies provided in this paper.

To detect tumor that has mainly these steps, segmentation, Classification, Pre-Processing, and Feature Extraction, image processing techniques are used. The flowchart of the steps followed in classification and tumor detection is shown in figure 1. Primary stage consists of group of MRI samples. MRI has different weighted images, Flair -Weighted, T2 Weighted, T-1 Weighted.

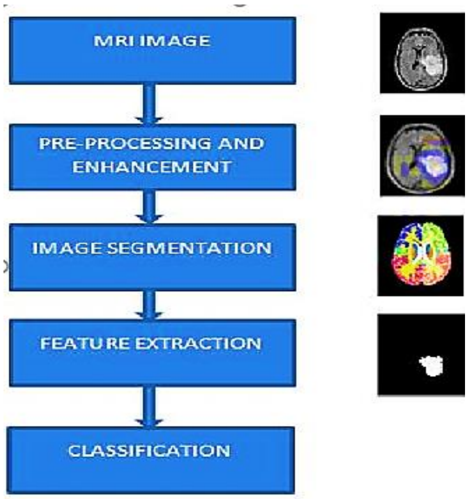

Fig 1. General Steps for Tumor Detection and Classification in Image Processing

To enhance the chances of detecting the suspicious region image processing first step is used. From the image noise is removed, and image is enhanced for finer details. Noise decreases the accurateness of the image when Clinical MRI corrupted. To remove this noise various filters are used. To remove background noise Anisotropic filter is used. To remove pepper and salt noise weighted median filter is used. Scaling coefficient biased and wavelet makes by Wavelet based de-noising technique.

Brain tumors are a heterogeneous gathering of focal sensory system neoplasms that emerge inside or nearby the cerebrum. Besides, the area of the tumor inside the cerebrum profoundly affects the patient's side effects, careful helpful choices, and the probability of acquiring an authoritative conclusion. The area of the tumor in the mind additionally especially changes the danger of neurological poison levels that adjust the patient's personal satisfaction.

ISSN: 0011-9342|Year2021
Issue: 9|Pages:7332-7344

As of now, cerebrum tumors are recognized by imaging solely after the beginning of neurological indications. No early discovery techniques are being used, even in people known to be in danger for explicit kinds of mind tumors by prudence of their hereditary cosmetics. Current histopathological characterization frameworks, which depend on the tumor's assumed cell of beginning, have been set up for almost a century and were refreshed by the world health organization in 1999.

Albeit good in numerous regards, they don't permit exact forecast of tumor conduct in the individual patient, nor do they control restorative dynamic as unequivocally as patients and doctors would expectation and need. Current imaging procedures give fastidious anatomical outline and are the chief instruments for building up those neurological manifestations are the outcome of a mind tumor.

The further chapters in paper includes chapter 2 as literature survey which has information related to previous research , chapter 3 is existing techniques which includes all state of art techniques for brain tumor detection and classification, in chapter 4 there is proposed method in detail explanation , chapter 5 includes results and further there is conclusion, applications , advantages.

II. Literature Survey

[1]. Deep learning by ian good fellow, yoshua bengio and aaron courville published by mit press, 2016

In deep learning and in general the deep learning textbook is a resource intended to help practitioners and students in the field of machine learning. The online version of the book will remain available online for free. An introduction to a broad range of topics in deep learning, covering conceptual background and mathematical. In a traditional feed-forward neural network, the images are fed into the net and the neurons process the images and classify them into the outputs of true and false likelihood.

[2]. Stanford university's course — cs231n: convolutional neural network for visual recognition by prof. Fei-fei li, justin johnson, serena yeung

In our society computer vision has become ubiquitous, with applications in self-driving cars, medicine, mapping, drones, search, apps. Core to several of these applications are visual acknowledgement tasks such as detection, localization, and classification. In neural

ISSN: 0011-9342|Year2021
Issue: 9|Pages:7332-7344

network current developments methods have significantly progressive the performance of these state-of-the-art visual recognition structures.

[3]https://datascience.stackexchange.com/questions/14349/difference-of-activation-functions-in-neural-networks-in-general

Based on the desired continuous or binary output activation function categories intended for neural networks have studied by me. The functions themselves are fairly straightforward, but the application modification is not entirely strong. One differentiates between linear type and logical functions is reasonable. For instance, it is difficult to understand Relu.

[4].Https://www.codementor.io/james_aka_yale/convolutional-neural-networks-the-biologically-inspired-model-iq6s48zms.

The field of computer vision tackles this exact problem, as machine learning researchers have focused extensively on object detection problems over time. There are various things that make it hard to recognize objects: image segmentation/deformation, lighting, affordances, viewpoint, huge dimensions, etc. In particular, computer vision researchers use neural networks to solve complex object recognition problems by chaining together a lot of simple neurons.

[5].Https://searchenterpriseai.techtarget.com/definition/convolutional-neural-network

In artificial neural network, convolutional neural network (cnn) is a type, these are used in image processing and image recognition to process pixel data, that is specifically designed. To perform both descriptive tasks and generative, artificial intelligence (ai), and cnns are powerful image processing often using machine vison that includes video and image recognition.

III. Existing System

A person's mentality The unusual improvement of tissues within the brain is what defines a tumour. Tumors are becoming more common than ever before. In 2016, an estimated 23,800 people (10,350 women and 13,450 men) in the United States were diagnosed with life-threatening brain and spinal tumours [2].

Because of the variety of shape, size, tumour area, and the existence and appearance of tumours inside the brain, analysing brain tumours is extremely difficult. Because the precise size of tumours cannot be seen, it is difficult to detect brain cancers at an early stage.

However, if a brain tumour is detected early on, the appropriate therapies can be implemented, and the tumour may be treatable. The use of scientific imaging methodologies for clinical analysis and clinical research has been facilitated by the visual depiction of the inside of the body. The most successful and widely used tool for detecting brain tumours is magnetic resonance imaging (MRI).

Current diagnosis tools have replaced the use of traditional procedures based on human experience, which raises the risk of false detection when determining the presence of brain tumours. Current equipment and approaches for studying tumours and their behaviour have become more known.

The image processing method might be utilized to detect brain cancers. Image processing technologies turn photographs into virtual images and perform operations on them in order to produce better and enhanced photographs [3]. This article looks at how image processing methods may be used to detect brain cancers. At the moment, clinical image processing is a vital and rapidly increasing subject.

It goes through many types of imaging methods. Magnetic Resonance Imaging (MRI), X-rays, and Computed Tomography scans (CT scans) are a few examples. These procedures are employed within the human body to detect even the tiniest flaws. Sports are regarded as a mental tumour within the mind that has an influence on the correct mind; they are produced by a distinctive rise in tissues.

The basic goal of scientific picture processing is to recognise relevant data using photographs that are correct and have the fewest possible errors. Due to its superior snapshots and high resolution in contrast to other imaging technologies, it is used to get malignant tissues and images of the human frame. Identifications from MRI pictures of the brain are tough due to the complexity of the mind.

It is possible to segment a brain tumour and analyse MRI images. These tumours may be segmented using a variety of picture segmentation algorithms. MRI images are used to identify brain cancers and are divided into four sections: function extraction, pre-processing, photograph categorization, and image segmentation.

Disease prognosis is usually done manually or with the help of rudimentary software tools that are often inaccurate and are only used as a reference. Although, with the advancement of contemporary techniques, the situation is changing, and computers are now

ISSN: 0011-9342|Year2021
Issue: 9|Pages:7332-7344

able to detect ailments more accurately than ever before. In certain circumstances, machines are even more accurate than humans, which is a significant scientific achievement.

Photograph processing has been used to process images in the medical circulate in conjunction with cellular detection in recent years. S. Mokhled [4] introduced various identification procedures in 2012, including segmenting snapshots to retrieve the item from history via the edge. This function is introduced with the 'Gabor filter out,' which allows for extra classification of cancer cells. In 2013, 'H. G. Zadeh' [5] presented additional techniques for identifying cancer cells, including picture extraction and segmentation.

Before using the 'Fast Fourier Transform,' the Gaussian smoothing notion was presented as a filtering rationale (FFT). Machine Learning is a term that refers to the study of 'NN' and 'Fuzzy' for tumour detection. For the detection of tumorous cells, C-suggest methods were developed [6]. While this reduces computing time, it also reduces accuracy. 'X. Chen introduced gene counting generation [7] in 2014. However, this approach is ideally suited to the complicated construction of gene selection.

This research study focuses on the detection of brain tumours utilising photos processing procedures, employing the techniques and technologies mentioned above. We discovered a few flaws in existing procedures, including the fact that current strategies are frequently reliant on the manual method that current systems have a greater run time complexity, and that current detection and kind of abnormalities accuracy is lower.

So, to overcome the problem, we used a strategy that is mostly based on deep mastering (CNN version), and it was assessed using the Python software programme.

IV. Proposed System

Proposed system is using machine learning algorithm which will be trained for detecting brain tumors. Neural Network and use Brain scan images for Training of the Neural Network. Finally, an UI based System is implemented using python software which will allow user to select the brain image and get the prediction results and graphs.

ISSN: 0011-9342|Year2021
Issue: 9|Pages:7332-7344

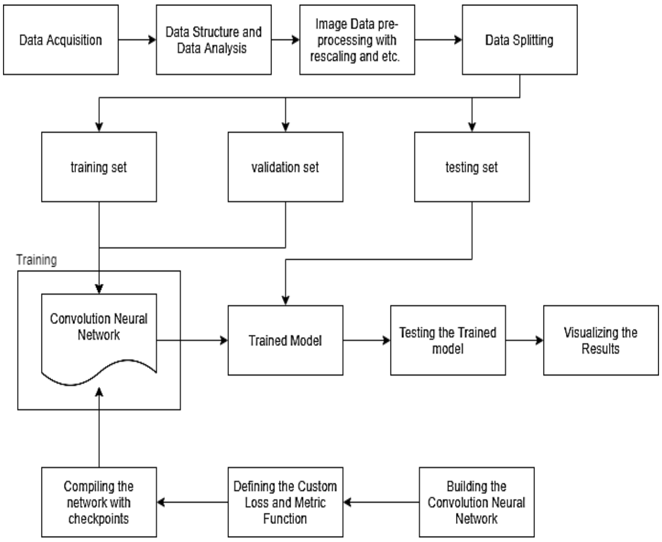

Fig.2 Block Diagram of proposed work (Proposed Architecture)

Proposed work has some important steps such as

a) Data acquisition
b) Data preprocessing
c) Data splitting
d) Training Convolutional Neural Network for training dataset
e) Testing the trained model for testing dataset
f) Performance analysis

Above all points are discussed in detail below,

a) Data Acquisition

In data acquisition, we selected the dataset with MRI scan images which has several normal and abnormal images. This is also called loading/ importing input data in workspace. The normal Image data can be converted to a file which can be understandable python data such as “nd-array” object of “numpy” object.

b) Data Preprocessing

Input images from the dataset are preprocessed to get standard dataset images which gives better improvement in results. Preprocessing is not a compulsory task but it improves the results by enhancing input image quality or rescaling input data. Pre-processing even includes augmentation , reshaping and rescaling also.

c) Data Splitting

Input dataset is splitted in training set, testing set and validation set. Training set is used for training the CNN model.

d) Training Convolutional Neural Network for Training Dataset

ISSN: 0011-9342|Year2021
Issue: 9|Pages:7332-7344

With the help of CNN hidden layers, CNN get trained using splitted training dataset. Convolutional neural network has layered structure which consists of different layers with optimization, metric function and loss function, running all models together helps in training CNN model.

e) Testing The Trained Model for Testing Dataset

Trained model is used to test new input testing image for tumor detection. In this step, we will visualize trained model Behaviour for new testing input image dataset and prediction of tumor output for given testing set.

f) Performance Analysis

Both subjective and objective performance analysis is used for understanding performance of proposed work. For objective analysis accuracy graph and loss graph is plotted.

CNN STRUCTURE

Our convolutional neural network has architecture as follows:

[INPUT] →[CONV 1] → [BATCH NORM] → [ReLU] → [POOL 1] → [CONV 2] → [BATCH NORM] → [ReLU] → [POOL 2] → [FC LAYER] → [RESULT]

We'll use a kernel of spatial dimension 5 x 5 with stride size 1 and padding of 2 for both conv layers. We'll utilize the max pool operation with kernel size 2, stride 2, and zero padding for both pooling layers.

```
________________________________________________________________
________________________________________________________________
Layer (type) Output Shape Param # Connected to
================================================================
================================================================
input_1 (InputLayer) [(None, 64, 64, 3)] 0
________________________________________________________________
________________________________________________________________
conv2d (Conv2D) (None, 64, 64, 64) 1792 input_1[0][0]
________________________________________________________________
________________________________________________________________
activation (Activation) (None, 64, 64, 64) 0 conv2d[0][0]
________________________________________________________________
________________________________________________________________
conv2d_1 (Conv2D) (None, 64, 64, 64) 36928 activation[0][0]
________________________________________________________________
________________________________________________________________
batch_normalization (BatchNorma (None, 64, 64, 64) 256
conv2d_1[0][0]
________________________________________________________________
________________________________________________________________
activation_1 (Activation) (None, 64, 64, 64) 0
batch_normalization[0][0]
________________________________________________________________
________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 32, 32, 64) 0
activation_1[0][0]
________________________________________________________________
________________________________________________________________
conv2d_2 (Conv2D) (None, 32, 32, 128) 73856
max_pooling2d[0][0]
________________________________________________________________
________________________________________________________________
activation_2 (Activation) (None, 32, 32, 128) 0
conv2d_2[0][0]
```

Fig.3 CNN structure used

This project addresses some of the challenging issues on brain magnetic resonance (MR) image tumour segmentation caused by the weak correlation between magnetic resonance imaging (MRI) intensity and anatomical meaning. With the objective of utilizing more

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Issue: 9|Pages:7332-7344

meaningful information to improve brain tumour segmentation, an approach which employs bilateral symmetry information as an additional feature for segmentation is proposed. This is motivated by potential performance improvement in the general automatic brain tumour segmentation systems which are important for many medical as well as scientific applications.

V. Results and Outputs

Proposed system is analyzed using python and open CV software and following results are obtained. Both subjective and objective analysis is performed to understand the detailed result analysis and performance of proposed system over state of art techniques.

5.1 Loss Graph

It is a Graph between Loss of CNN and Number of Epochs.

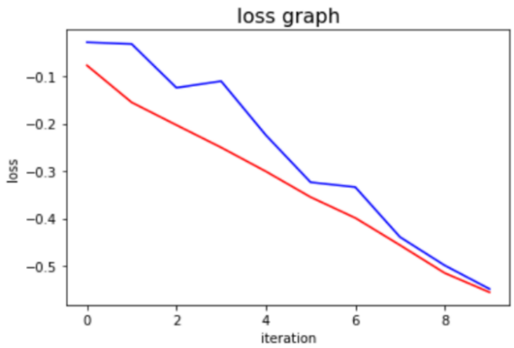

Fig.4 Iteration vs Loss graph

At given epoch loss measure is calculated and across data items loss function is calculated during present epoch. With respect to iteration loss in the subset of complete dataset is calculated.

5.2 Accuracy Graph

It is a Graph between Accuracy of CNN and Number of Epochs.

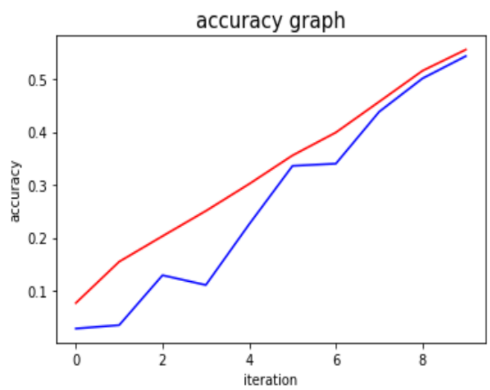

Fig.5 Iteration Vs Accuracy performance is plotted

Performance of proposed work, accuracy is plotted for different iterations. We can see that w.r.t. iterations accuracy is increasing. Comparison with true data, how much precisely proposed model is working is shown by this graph.

The outputs for the given testing image are as, leftmost is original input image, second is groundtruth image, third image is overlapped image of both input and predicted image for better understanding, last image is the predicted image.

5.3 Results of Testing Images

Here we took 3 different test images and results are analyzed with both subjective and objective analysis.

a) Results for Testing Image 1

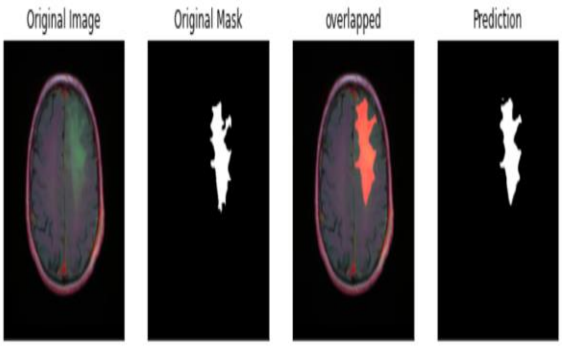

Fig.6 For testing image 1, a) Original Image b) Original Mask c) Overlapped image d) Prediction

b) Results for Testing Image 2

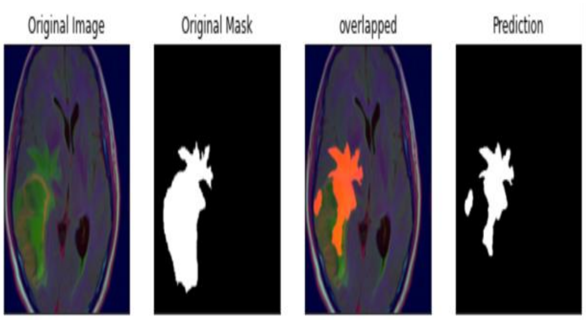

Fig.7 For testing image 2, a) Original Image b) Original Mask c) Overlapped image d) Prediction

c) Results for Testing Image 3

ISSN: 0011-9342|Year2021

Issue: 9|Pages:7332-7344

Fig. For testing image 3, a) Original Image b) Original Mask c) Overlapped image d) Prediction

Advantages

There are many advantages of proposed deep learning algorithm over other state of art techniques as mentioned below,

1. Advance Machine Learning (Deep Learning) technique is used
2. Low run time complexity
3. Higher accuracy over the state of art techniques
4. It can work even for more complex MRI scan image
5. As user friendly UI is prepared, users can use easily without much knowledge of software

Applications

There are many applications of proposed work in medical field,

1. Smart Hospitality
2. For doctors, while giving prescription and patient also can understand easily.
3. Smart MRI can be provided to patient which has all the detailed information about abnormality

Conclusion

Proposed work is successfully designed and results are analyzed using python software. Deep learning is used for detection of brain tumor from MRI image. Preprocessing is applied on input dataset to get standard images in standard format and preprocessed input dataset is splited into training set, testing set and validation set. CNN is used for training and testing dataset for prediction of tumor region. Python and machine learning toolboxes used for further detection of area where tumor is located. Proposed work helps to analyze the input MRI scan abnormal part. Proposed work is having many advantages over the state of art techniques such as low run time complexity, higher accuracy.

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