AUTOMATED SEGMENTATION OF BRAIN TUMOUR MRI IMAGES USING DEEP LEARNING

A PROJECT REPORT

PHASE 1

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BONAFIDE CERTIFICATE

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

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ABSTRACT

A brain tumor is understood by the scientific community as the growth of abnormal cells in the brain, some of which can lead to cancer. The traditional method to detect brain tumors is nuclear magnetic resonance (MRI). Having the MRI images, information about the uncontrolled growth of tissue in the brain is identified Brain tumor detection is done through the application of Machine Learning and Deep Learning algorithms. VGG16 are applied in the detection of the presence of brain tumor, and its performance is analyzed through different metricsIn proposed on LSTM Algorithm The aggressive nature and diversity of gliomas, well-organized and exact segmentation methods used to classify tumors. Merging the result of two separate segmentation networks the method demonstrates a major but simple combinational strategy. By the whole tumor enhanced tumor, and tumor core will define the validation set. Segmenting brain tumors by using MR data for disease investigation and monitoring. Segmenting brain tumors automatically using MR data is crucial for disease investigation and monitoring. Due to the aggressive nature and diversity of gliomas, well-organized and exact segmentation methods are used to classify tumors intra-tumorally.

Keywords:

Brain tumor detection, MRI images, DL, CNN model, image classification

LIST OF FIGURES

LIST OF ABBREVIATIONS

ACRONYM		ABBREVIATION
ANN	-	Artificial Neural Network
CNN	-	Convolutional Neural Network
VPT	-	Vintage Point Tree
GLCM	-	Grey Level Co-Occurance Matrix
BTCCNN	-	Brain Tumor Classification CNN
ERT	-	Extremely Randomized Trees
RELU	-	Rectified Linear Unit
MRI	-	Magnetic Resonance Image
MDS	-	Medical Detection Systems

CHAPTER 1

INTRODUCTION

1.1 BRAIN TUMORS

Brain tumors can be classified into two types: benign (noncancerous) and malignant (cancerous). The malignant tumors can quickly spread to other tissues in the brain and lead to worsening the patient's condition . When most of the cells are old or damaged, they are destroyed and replaced by new cells. if damaged and old cells are not eliminated with generating the new cells, it can cause problems.

The production of additional cells often results in the formation of a mass of tissue, which refers to the growth or tumor. Brain tumor detection is very complicated and difficult due to the size, shape, location and type of tumor in the brain. Diagnosis of brain tumors in the early stages of the tumor's start is difficult because it cannot accurately measure the size and resolution of the tumor .

However, if the tumor is diagnosed and treated early in the tumor formation process, the chance of patient's treatment is very high. Therefore, the treatment of tumor depends on the timely diagnosis of the tumor .

The diagnosis is usually done by a medical examination, with computer tomography or magnetic imaging. MRI imaging is a method that provides accurate images of the brain and is one of the most common and important methods for diagnosing and evaluating the patient's brain. In the field of Medical Detection Systems (MDS), MRI images provide better results than other imaging techniques such as Computed Tomography (CT), due to their higher contrast in soft tissue in humans . The proposed technique has used CNN to identify and categorize the tumor from brain images of the brain.

1.2 CONVOLUTIONAL NEURAL NETWORK

The main difference between the main channel of the neural network with the normal neural network is that it is able to automatically and locally extract the feature from each image . These types of networks consist of neurons with weights and biases that can be learned . Due to the results of CNN on the dataset, in order to improve the proposed method. Machine learning algorithm is used to feature extraction. The algorithm used was the clustering algorithm applied on data set, and then the images are applied to the CNN. The results showed that the proposed method has been successful.

The purpose of extracting the property before applying to the CNN is that in some images fatty masses are considered as tumors, or in some images the tumor is mistakenly considered to be fat and should have increased medical error. Extracting the attribute initially and before applying the CNN leads to improved network accuracy and increased accuracy In , an automated method is used to identify and categorize MRI images.

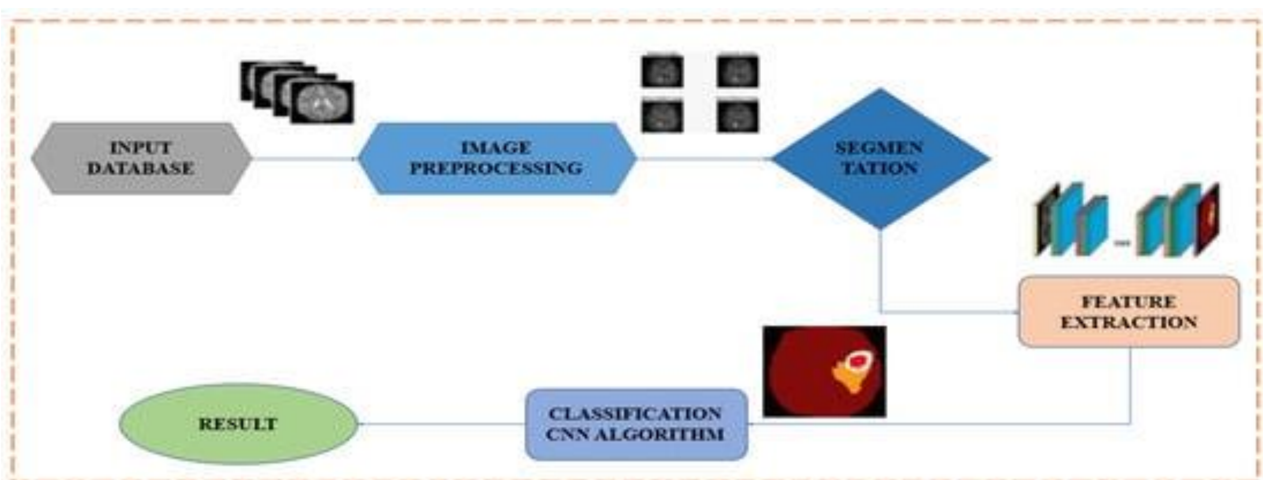

FIGURE NO: 1.2 Methodology for BT segmentation using CNN.

This method is based on the Super Pixel Technique and the classification of each Super Pixel. Extremely randomized trees (ERT) classifier is compared with SVM to classify each super pixel into tumor and normal. This method has two datasets, which are 19 MRI FLAIR images and BRATS 2012 dataset.

The results demonstrate the good performance of this method using ERT classifier. In , an automatic classification method is used to identify a tumor using a CNN with 3 × 3 small kernels. The method obtained simultaneously the first position for the complete, core, and enhancing regions in dice similarity, coefficient metric (0.88, 0.83, 0.77), at the BRATS Challenge 2013. In , Alex net model CNN is used to simultaneously diagnose MS and normal tumors. The CNN was able to accurately classify 98.67% images correctly into three classes.

In , a multi-stage Fuzzy C-Means (FCM) framework was proposed to segment brain tumors from MRI images. In , An efficient and effective method which uses CNNs used for classification and segmentation. The proposed method, used Image Net for extract features. The results obtained 97.5% accuracy for classification and 84% accuracy for segmentation. In [, multiphase MRI images in tumor grading have been studied and a comparison has been made between the results of deep learning structures and base neural networks. The results show that the network performance based on the sensitivity and specificity of CNN improved by 18% compared to the neural networks

1.3 Project Objectives

- To enhance the performance of the earliest possible prediction.
- To increase the accuracy of the Classification results.
- To enhance the performance of the overall prediction results.

1.4 Problem Statement

- Overcomes have a seizure, head injury, toxic exposure, facial dimorphic features, and the evidence of genetic, metabolic, or infectious disorders

CHAPTER 2
LITERATURE REVIEW

2.1 LITERATURE SURVEY

2.1.1 Title: Revalence of Autism Spectrum Disorder Among Children Aged 8 Years Autism and Developmental Disabilities Monitoring Network.

Year: 2014

Author: N.V. Ramana Murty and Prof. M.S. Prasad Babu

Methodology:

The Autism and Developmental Disabilities Monitoring (ADDM) Network is an active surveillance system that provides estimates of the prevalence of autism spectrum disorder (ASD) among children aged 8 years whose parents or guardians reside within 11 ADDM sites in the United States (Arizona, Arkansas, Colorado, Georgia, Maryland, Minnesota, Missouri, New Jersey, North Carolina, Tennessee, and Wisconsin). ADDM surveillance is conducted in two phases. The first phase involves review and abstraction of comprehensive evaluations that were completed by professional service providers in the community. Staff completing record review and abstraction receive extensive training and supervision and are evaluated according to strict reliability standards to certify effective initial training, identify ongoing training needs, and ensure adherence to the prescribed methodology. Record review and abstraction occurs in a variety of data sources ranging from general pediatric health clinics to specialized programs serving children with developmental disabilities. In addition, most of the ADDM **.**

Advantage

- In direct outgrowth of this study was a favourable recommendation for CT-based Brain Tumor screening by several prestigious organizations.

Disadvantage

- Administrative costs to be high
- Lack of Real-Time Data.

2.1.2 Title : ALE meta-analysis workflows via the BrainMap DATABASE : progress towards a probabilistic functional brain atlas

Author: Harleen Kaur and Siri Krishan Wasan

Year: 2016

Methodology:

With the ever-increasing number of studies in human functional brain mapping, an abundance of data has been generated that is ready to be synthesized and modeled on a large scale. The BrainMap database archives peak coordinates from published neuroimaging studies, along with the corresponding metadata that summarize the experimental design. BrainMap was designed to facilitate quantitative meta-analysis of neuroimaging results reported in the literature and supports the use of the activation likelihood estimation (ALE) method. In this paper, we present a discussion of the potential analyses that are possible using the BrainMap database and coordinate-based ALE meta-analyses, along with some examples of how these tools can be applied to create a probabilistic atlas and ontological system of describing function–structure correspondences

Advantage

- These systems can offer a great variety of channels and workspaces to facilitate information sharing and communication between healthcare department.
- Large-Scale Data Synthesis and Quantitative Meta-Analysis.

Disadvantage

- Most of the current data mining tools are too complex for use by Healthcare systems.
- The database may be subject to publication bias, as studies with statistically significant or novel findings are more likely to be published. This bias could affect the generalizability of meta analytic results

2.3.3 Title: Development of functional and structural connectivity within the default mode network in young children

Year: 2016

Author: Samy S. Abu Naser, Bashar G. Bastami

Methodology:

Functional and structural maturation of networks comprised of discrete regions is an important aspect of brain development. The default-mode network (DMN) is a prominent network which includes the posterior cingulate cortex (PCC), medial prefrontal cortex (MPFC), medial temporal lobes (MTL), and angular gyrus (AG). Despite increasing interest in DMN function, little is known about its maturation from childhood to adulthood. Here we examine developmental changes in DMN connectivity using a multimodal imaging approach by combining resting-state fMRI, voxel-based morphometry and diffusion tensor imaging-based tractography. We found that the DMN undergoes significant developmental changes in functional and structural connectivity, but these changes are not uniform across all DMN nodes. Convergent structural and functional connectivity analyses suggest that PCC-mPFC connectivity along the cingulum bundle is the most immature link in the DMN of children. Both PCC and mPFC also showed gray matter volume differences, as well as prominent macrostructural and microstructural differences in the dorsal cingulum bundle linking these regions. Notably, structural connectivity between PCC and left MTL was either weak or non-existent in children, even though functional connectivity did not differ from that of adults.

Advantage

- Still effective in cases where number of dimensions is greater than the number of samples.
- Uses a subset of training points in the decision function so it is also memory efficient.

Disadvantage

- It is time complexity being high, and not suitable for large-scale data.

CHAPTER 3
SYSTEM ANALYSIS

3.1 Existing System

- Many methods have achieved good classification results in the classification of images. This Existing review of the classification methods of images from three aspects supervised classification, semi-supervised classification, and unsupervised classification
- It is based on the CNN Algorithm Automated segmentation of brain tumor MRI images using deep learning is a significant area of research in medical image analysis. Several existing systems and approaches have been developed to address this challenge.
- Acquire a dataset of brain MRI images with corresponding ground truth annotations for tumor regions. Databases like BRATS (Multimodal Brain Tumor Segmentation Challenge) are commonly used.
- Perform preprocessing on the MRI images to enhance features and standardize the input data. This may involve skull stripping, intensity normalization, and image registration.

3.1.1 ALGORITHM

- Convolution filters, pooling layers, and a feed-forward neural network are all part of this CNN classification system.
- Convolutional kernels or filters transform pictures into feature map data. Kernels of data (height, length, and depth) flow across three dimensions in a 3D CNN, creating 3D maps.
- It is essential to use a 3D CNN to analyze data that has a temporal or volumetric context.

3.1.2 LIMITATIONS

- Limited diverse data and insufficient data.
- Deep learning models may be sensitive to variations in image acquisition parameters, such as different MRI machines, imaging protocols, or contrasts.
- Adaptation to new variants in Deep learning models may struggle to adapt to new variants of tumors or unforeseen pathological characteristics that were not adequately represented in the training data.
- These limitations requires ongoing research and collaboration between computer scientists, medical professionals, and ethicists to develop more robust, interpretable, and clinically reliable deep learning models for automated brain tumor segmentation.
- Transitioning from research environments to practical clinical applications requires rigorous testing and validation to ensure reliability and safety.

3.2 PROPOSED SYSTEM

- In this proposed using Segmentation on Rest50 Algorithm It is based on using the LSTM Algorithm for the prediction on Tumor part.
- On the other hand, LSTM (Long Short-Term Memory) is a type of recurrent neural network (RNN) commonly used for sequential data, such as time series.
- Using LSTM for predicting tumor progression or changes over time in a sequence of MRI images, could be a valid approach.
- Adapt the ResNet-50 architecture for semantic segmentation by converting fully connected layers into convolutional layers. Train the modified ResNet-50 on the brain MRI dataset for tumor segmentation.

3.2.1 ALGORITHM

- Design the architecture with encoder and decoder components. U-Net, SegNet, and DeepLab are popular architectures for medical image segmentation.
- Define a loss function that measures the difference between the predicted segmentation and the ground truth.
- Train the model using the training set, validating on the validation set to monitor performance and prevent overfitting.
- Post-processing techniques to refine the segmentation results. This may include smoothing, removing small connected components, or other morphological operations.

3.2.2 Advantages

- High performance
- CNN is improving the accuracy using Liver images.
- Less time duration
- Early detection of tumors

CHAPTER 4
SYSTEM REQUIREMENTS

4.1 Hardware Requirements

The section of hardware configuration is a very important task associated with the software development in sufficient random access memory may affect adversely on the speed and efficiency of the complete system .The method should be powerful to handle the complete operations

- System : Pentium IV 2.4 GHz
- Hard Disk : 200 GB
- Mouse : Logitech.
- Keyboard : 110 keys enhanced
- Ram : 4GB

4.2 Software Requirements

A serious element in building a system is that the section of compatible software since the software within the market is experiencing in progression. Selected software should be acceptable by the firm and one user additionally because it should be feasible for the system.

- O/S : Windows 7.
- Language : Python
- Front End : Anaconda Navigator – Spyder

4.3 Software Description:

Python

Python is one of those rare languages which can claim to be both simple and powerful. You will find yourself pleasantly surprised to see how easy it is to concentrate on the solution to the problem rather than the syntax and structure of the language you are programming in. The official introduction to Python is Python is an easy to learn, powerful programming language. It has efficient high-level data structures and a simple but effective approach to object-oriented programming. Python's elegant syntax and dynamic typing, together with its interpreted nature, make it an ideal language for scripting and rapid application development in many areas on most platforms.

FIGURE NO:4.3.1 PYTHON LOGO

Features of Python

Simple

Python is a simple and minimalistic language. Reading a good Python program feels almost like reading English, although very strict English! This pseudo-code nature of Python is one of its greatest strengths. It allows you to concentrate on the solution to the problem rather than the language itself.

Easy to Learn

As you will see, Python is extremely easy to get started with. Python has an extraordinarily simple syntax, as already mentioned.

Free and Open Source

Python is an example of a FLOSS (Free/Libré and Open Source Software). In simple terms, you can freely distribute copies of this software, read its source code, make changes to it, and use pieces of it in new free programs. FLOSS is based on the concept of a community which shares knowledge. This is one of the reasons why Python is so good - it has been created and is constantly improved by a community who just want to see a better Python.

High-level Language

When you write programs in Python, you never need to bother about the low-level details such as managing the memory used by your program, etc.

Portable

Due to its open-source nature, Python has been ported to (i.e. changed to make it work on) many platforms. All your Python programs can work on any of these platforms without requiring any changes at all if you are careful enough to avoid any system-dependent features. You can use Python on GNU/Linux, Windows, FreeBSD, Macintosh, Solaris, OS/2, Amiga, AROS, AS/400, BeOS, OS/390, and # -*- coding: utf-8 -*-z/OS, Palm OS, QNX, VMS, Psion, Acorn RISC OS, VxWorks, PlayStation, Sharp Zaurus, Windows CE and PocketPC! You can even use a platform like Kivyto create games for your computer and for iPhone, iPad, and Android.

Interpreted

A program written in a compiled language like C or C++ is converted from the source language i.e. C or C++ into a language that is spoken by your computer (binary code i.e. 0s and 1s) using a compiler with various flags and options. When you run the program, the linker/loader software copies the program from hard disk to memory and starts running it. Python, on the other hand, does not need compilation to binary. You just run the program directly from the source code. Internally, Python converts the source code into an intermediate form called byte codes and then translates this into the native language of your computer and then runs it. All this, actually, makes using Python much easier since you don't have to worry about compiling the program, making sure that the proper libraries are linked and loaded, etc. This also makes your Python programs much more portable, since you can just copy your Python program onto another computer and it just works!

Object Oriented

Python supports procedure-oriented programming as well as object-oriented programming. In procedure-oriented languages, the program is built around procedures or functions which are nothing but reusable pieces of programs. In object-oriented languages, the program is built around objects which combine data and functionality.

Embeddable

You can embed Python within your C/C++ programs to give scripting capabilities for your program's users.

CHAPTER 5
SYSTEM ARCHITECTURE

We suggest an MRI image-based BT classification technique that is completely automated. The specified objective is to categorize three different forms of cancers in brain scans, including gliomas and pituitary tumors, using a three-class classification problem. These three BT types are the most prevalent. A DCNN with a U-Net sampling model is used for classification, as well as to extract image features. The open dataset from Fig share is used in the evaluation. Our work is motivated by the following factors: First, greater accuracy in the categorization problem involving meningiomas, gliomas, and endocrine tumors is expected. Medical professionals' treatment regimens would benefit from a precise, computer-aided automatic classification approach for the three different types of tumors. Second, recent classification challenges that employed DL techniques and reliable classifiers were successful in producing highly accurate results. Medical imaging data are hard to attain, which is the third issue. To overcome this practical restriction, advanced design techniques are needed.

The following are the contributions made by this work:

- To extract characteristics from brain MRI images containing tumors, a CNN model was created.
- On datasets containing medical images, it was discovered that the CNN layout produced better classification results.
- The feature maps are produced after numerous convolutional layers have extracted features from the input images.
- The BraTS dataset was used to create a model with 98% overall accuracy;
- Regarding computational complexity, a comparison between the proposed approach and a transfer learning-based strategy is given.

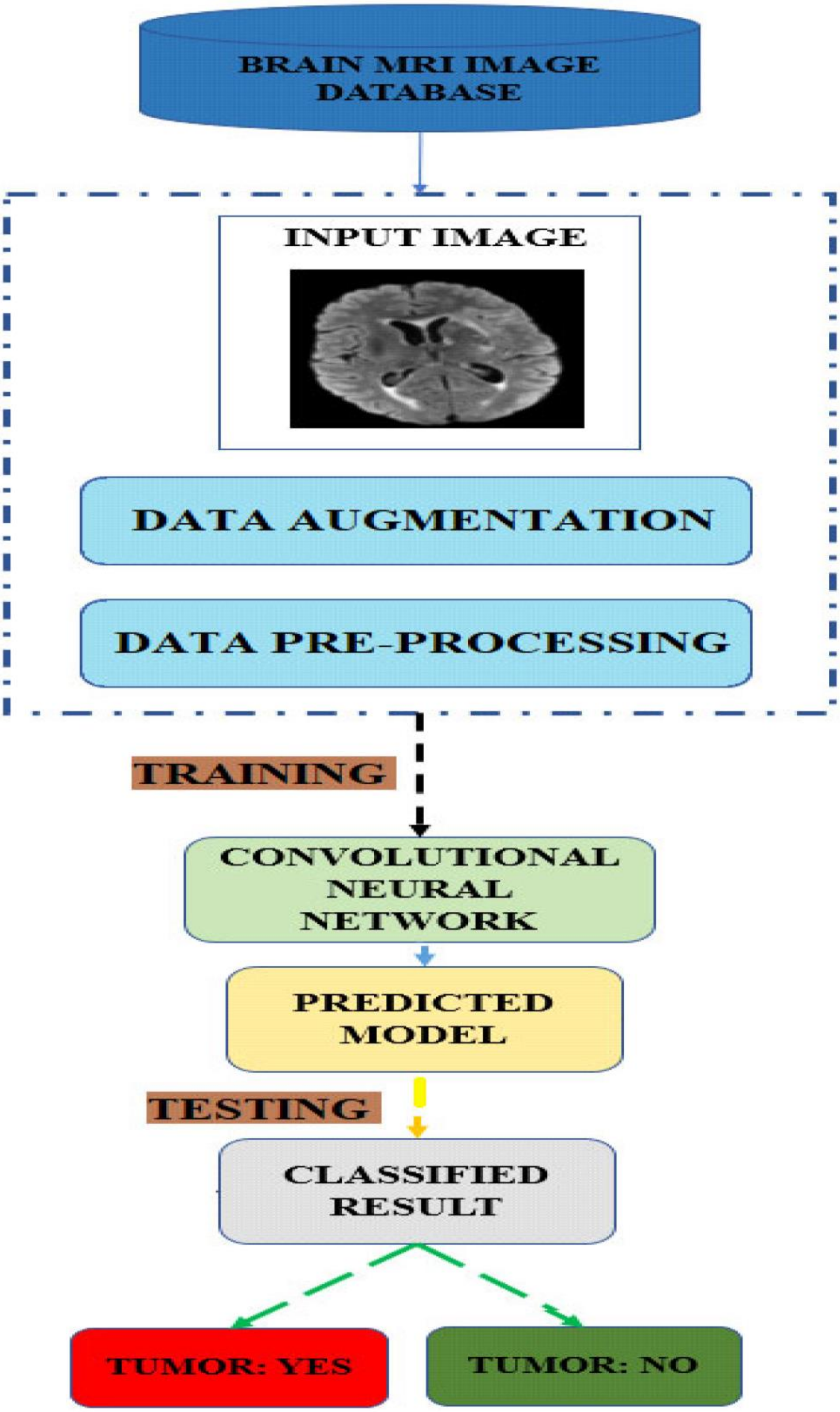

FIGURE NO: 5.1 SYSTEM ARCHITECTURE

CHAPTER 6
MODULES

6.1 LIST OF MODULES

- Brain Image
- Segmentation
- Splitting Dataset into Train and Test Data
- Classification
- Prediction
- Result Generation

6.2 MODULES DESCRIPTION

BRAIN IMAGE

- The data selection is the process of selecting the data for Brain Image dataset.
- In this project, detect the Brain Tumor .The dataset which contains the information about the Brain grayscale images

SEGMENTATION

- ResNet-50 is a convolutional neural network that is 50 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database .Tumor detection part

SPLITTING DATASET INTO TRAIN AND TEST DATA

- Data splitting is the act of partitioning available data into two portions, usually for cross-validate purposes.
- One Portion of the data is used to develop a predictive model and the other to evaluate the model's performance.
- Separating image data into training and testing sets is an important part of evaluating image processing models.

CLASSIFICATION

In Deep learning, a **convolutional neural network** (**CNN/ConvNet**) is a class of deep neural networks, most commonly applied to analyse visual imagery. Now when we think of a neural network we think about matrix multiplications but that is not the case with ConvNet.. Now in mathematics **convolution** is a mathematical operation on two functions that produces a third function that expresses how the shape of one is modified by the other.

PREDICTION

- It's a process of predicting the Brain Tumor from the dataset.
- This project will effectively predict the data from dataset by enhancing the performance of the overall prediction results.

RESULT GENERATION

The Final Result will get generated based on the overall classification and prediction. The performance of this proposed approach is evaluated using some measures like,

- Accuracy
- Precision
- Recall
- F1-score

CHAPTER 7
CONCLUSION AND FUTURE ENHANCEMENT

7.1 Conclusion

In DL a **LSTM** is a class of DL , most commonly applied to analyse visual imagery. Now when we think of a neural network we think about matrix multiplications but that is not the case with ConvNet. It uses a special technique called Convolution. Now in mathematics **convolution** is a mathematical operation on two functions that produces a third function that expresses how the shape of one is modified by the other.

Multimodal MRI brain tumor image segmentation task, segmenting the entire tumor and tumor core area, enhanced tumor area from normal brain tissue. The research on computer-aided diagnosis and treatment of multimodal MRI brain tumor image segmentation has always been an important topic in the field of medical image processing. The difference in imaging equipment and imaging conditions will cause even the same patient in the same period to have a different MRI with different properties

7.2 Future Enhancement

In the future, different dataset will be investigated to check the system robustness and more CNN models will be tested to improve the performance and identification of smallest tumors

CHAPTER 8

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