

Brain Tumor Detection Using CNN

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ABSTRACT

This paper presents a comprehensive approach for brain tumor detection using a dataset comprising MRI images. The process involves dataset preprocessing, splitting into training and testing sets, image extraction, and labelling. A Convolutional Neural Network (CNN) model with 23 layers is proposed for the detection task, alongside an exploration of the VGG16 model for comparison. The CNN architecture is meticulously designed to extract intricate features from the MRI images. The proposed model's architecture and performance are thoroughly analysed and compared with the VGG16 model. Results indicate promising detection accuracy, demonstrating the effectiveness of the proposed approach in aiding medical professionals in diagnosing brain tumors accurately and efficiently. Furthermore, insights gained from the reflection on the 23 layers CNN architecture provide valuable perspectives for future advancements in medical image analysis using deep learning techniques. Finally it uses deep learning based Depth wise Separable Convolution Neural Network to detect the tumor based on the MRI images.

Keywords : Brain tumor detection, Dataset, Image extraction, Convolutional Neural Network, MRI images

I. INTRODUCTION

Medical imaging is the technique and process of creating visual representations of the interior of a body for clinical analysis and medical intervention, as well as visual representation of the function of some organs or tissues. Medical imaging seeks to reveal internal structures hidden by the skin and bones, as

well as to diagnose and treat disease. Medical imaging also establishes a database of normal anatomy and physiology to make it possible to identify abnormalities. The medical imaging processing refers to handling images by using the computer. This processing includes many types of techniques and operations such as image gaining, storage, presentation, and communication. This process

pursues the disorder identification and management. This process creates a data bank of the regular structure and function of the organs to make it easy to recognize the anomalies. This process includes both organic and radiological imaging which used electromagnetic energies (X rays and gamma), sonography, magnetic, scopes, and thermal and isotope imaging. There are many other technologies used to record information about the location and function of the body. Those techniques have many limitations compared to those modulates which produce images.

The brain tumor is one all the foremost common and, therefore, the deadliest brain diseases that have affected and ruined several lives in the world. Cancer is a disease in the brain in which cancer cells ascends in brain tissues. Conferring to a new study on cancer, more than one lakh people are diagnosed with brain tumors every year around the globe. Regardless of stable efforts to overcome the complications of brain tumors, figures show unpleasing results for tumor patients. To contest this, scholars are working on computer vision for a better understanding of the early stages of tumors and how to overcome using advanced treatment options. Magnetic resonance (MR) imaging and computed tomography (CT) scans of the brain are the two most general tests to check the existence of a tumor and recognize its position for progressive treatment decisions. These two scans are still used extensively for their handiness, and the capability to yield high-definition images of pathological tissues is more. At present, there are several other conducts offered for tumors, which include surgery, therapies such as radiation therapy, and chemotherapy. The decision for which treatment relies on the many factors such as size, kind, and grade of the tumor present in the MR image. It's conjointly chargeable for whether or not cancer has reached the other portions of the body.

A brain tumor is defined as abnormal growth of cells within the brain or central spinal canal. Some tumors

can be cancerous thus they need to be detected and cured in time. The exact cause of brain tumors is not clear and neither is exact set of symptoms defined, thus, people may be suffering from it without realizing the danger. Primary brain tumors can be either malignant (contain cancer cells) or benign (do not contain cancer cells). Brain tumor occurred when the cells were dividing and growing abnormally. It is appearing to be a solid mass when it diagnosed with diagnostic medical imaging techniques. There are two types of brain tumor which is primary brain tumor and metastatic brain tumor. Primary brain tumor is the condition when the tumor is formed in the brain and tended to stay there while the metastatic brain tumor is the tumor that is formed elsewhere in the body and spread through the brain.

II. LITERATURE SURVEY

[1] Capsule Networks for Brain Tumor Classification Based On MRI Images And Coarse Tumor Boundaries. As stated by the WHO, cancer is deemed to be second leading cause of human casualties. Out of different types of cancer, brain tumor is perceived as one of the fatal due to its vigorous nature, diverse characteristics and relatively low survival rate. Discovering the type of brain tumor has remarkable impact on the choice of therapy and patient's survival. Human based identification is usually inaccurate and unreliable leading in a recent sweep of interest to automatize this process using convolutional neural network (CNN). As CNN fails to completely utilize spatial relations, which may lead to incorrect tumor classification. In our technique, we have included newly evolved CapsNet to prevail this shortcoming. The main offering is to provide CapsNet with access to tissues neighbouring the tumor, without diverting it from the principal target. An improved CapsNet architecture is consequently proposed for the classification of brain tumor, that takes the coarse boundaries of tumor as additional input within its pipeline for surging the focus of the CapsNet.

[2] A Hybrid Feature Extraction Method with Regularized Extreme Learning Machine for Brain Tumor Classification

Classification of the brain tumor is the crucial step that depends upon understanding and expertise of the physician. The automated classification system of the brain tumor is vital to assist radiologists and physicians to identify the tumor. Nonetheless, the precision of the current systems needs to be improved for the successful treatment. In this paper the proposed approach consists of, (1) brain image pre-processing, (2) feature extraction of the image & (3) brain tumor classification. Initially the input images of the brain are transformed into intensity brain images using minmax normalization rule resulting into enhanced and improved contrast of the edges and regions of the brain. Then by applying feature extraction to the brain images using hybrid feature extraction and then computing the covariance matrix of the features extracted to project them into a notable set of features using principle component analysis (PCA). Ultimately, the type of brain tumor is classified using regularized extreme learning machine (RELM). As per the results the suggested approach proved to be more effectual compared to the current approaches. Also the performance in terms of accuracy of the classification improved from 91.51% to 94.233% for the experiment.

[3] Tumor Detection and Classification of MRI Brain Image using Different Wavelet Transforms and Support Vector Machines

The brain is the principal organ of human body. An abnormal growth of cells leads to the brain tumor. This abnormal growth of cells results in unusual functioning of brain and eradication of healthy cells. The brain tumors can be classified as malignant(cancerous) and benign(noncancerous) tumors. In this paper the proposed approach includes (1) Pre-processing, (2) Training the SVM & (3) Submit training set to SVM and output the obtained predictions. At first stage denoising the medical

images using different kind of wavelets while maintaining the important features. In segmentation for the extraction of the features, Otsu method is used for converting grey-level image to binary image. Finally, the data has two classes and we can apply SVM for classification. The outcome shows that SVM with proper training dataset is able to differentiate between normal and abnormal tumor regions and categories as malignant tumor, benign tumor or a healthy brain.

[4] Segmentation and Recovery of Pathological Mr Brain Images Using Transformed Low-Rank and Structured Sparse Decomposition

A general framework is proposed for the concurrent segmentation and recovery of pathological magnetic resonance images (MRI), where low rank and sparse decomposition (LSD) schemes have been used extensively. Due to the lack of constraint between low-rank and sparse components, conventional LSD techniques often construct recovered images with distorted pathological areas. For resolving this issue, a transformed low rank and structured sparse decomposition (TLS2D) method is proposed, that is vigorous for taking out pathological regions. By using structured sparse and computed image saliency as adaptive sparsity constraint the well recovered images can be acquired. The exploratory results on the MRI images of brain tumor shows that the TLS2D can successfully provide adequate performance on image recovery as well as tumor segmentation.

[5] Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images

Out of different types of brain tumors, malignant tumors are assertive and commonly occurring, decreasing the life expectancy. MRI is extensively used imaging method for assessing the tumors. Due to the huge amount of data produced by MRI stops the manual segmentation in a fair time, restricting the use of accurate quantitative measurements in clinical practices. For resolving this, an automatic segmentation technique based on CNN is proposed,

exploring small kernels. Employing small kernels allows designing a deeper architecture, alongside having an advantage against overfitting, given the small number of weights in the network. Use of intensity normalization in pre-processing with data augmentation has proven to be effectual for brain tumor segmentation in MRI images.

[6]Development of Automated Brain Tumor Identification Using MRI Images

Brain tumor is a prime reason for human casualties every year. Magnetic resonance imaging (MRI) is a commonly used technique for brain tumor diagnosis. An automated approach which incorporates enhancement at an early stage to reduce gray scale colour variations. For better segmentation the unnecessary noises were decreased as much as possible using filter operation. The proposed approach uses threshold-based Otsu segmentation rather than colour segmentation. Ultimately, the feature information provided by the pathology experts was used to identify region of interests. The exploratory results demonstrate that the proposed approach was able to provide adequate results as compared to present available approaches in terms of accuracy.

[7] Brain Tumor Segmentation to Calculate Percentage Tumor Using MRI

Brain tumor is a type of disease that damages the brain through an uncontrolled growth of cells. The details of the brain tumor is obtained through MRI. For giving right treatment the analysis of the tumor must be performed accurately. Segmentation method is used for the purpose of analysis, and is done to distinguish the brain tumor tissue from other tissues such as fat, edema and normal tissue. The MRI image must be maintained at the edge of the first image with median filtering, followed by segmentation process that requires thresholding. Segmentation process is performed by giving a mark on the area of the brain and area outside the brain using watershed method then clearing the skull with cropping. 14 brain tumor images are used as an input in this study. The segmentation result compares brain tumor.

III. EXISTING METHOD

Brain tumor detection with segmentation-based machine learning technique: As a large volume of medical MRI imaging data is gathered through image acquisition, the researchers are now proposing different machine learning methods to identify brain tumors.

Brain tumor detection through transfer learning: Transfer learning does well when the volume of data is limited since such a model is previously trained on a large dataset (e.g., the ImageNet database), containing millions of images. Another benefit is that it does not require a massive amount of computational resources since only the model's fully connected layers need to be trained.

IV. PROPOSED METHOD

Brain Tumor Classification Using Convolutional Neural Network:

Classification is the best approaches for identification of images like any kind of medical imaging. All classification algorithms are based on the prediction of image, where one or more features and that each of these features belongs to one of several classes. An automatic and reliable classification method Convolutional Neural Network (CNN) will be used since it is robust in structure which helps in identifying every minute details. A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNet have the ability to learn these filters/characteristics. The "23-layer CNN" framework provides segmentation-free feature extraction techniques that do not require any handcrafted feature extraction method relative to the

conventional machine learning methods. In this model, we replace the fully connected layers with four dense layers which facilitate tuning process. Data imbalance issue is solved in the Harvard Medical dataset by taking an almost equal number of MRI slices in both normal and abnormal tumor classes. The overfitting issue is solved in this study by increasing the number of MRI slices using a data augmentation strategy and introducing the dropout layers within both models. The proposed block diagram is shown in figure 1. The proposed “23-layers CNN” framework performance is evaluated on both large and small datasets. Results indicate that our framework is able to outperform previous studies found in the literature. To prevent overfitting in a small image dataset, we merged the “23-layers CNN” framework with the transfer learning-based VGG16 model. Results show that the suggested technique performs splendidly in the test images without experiencing any overfitting problems.

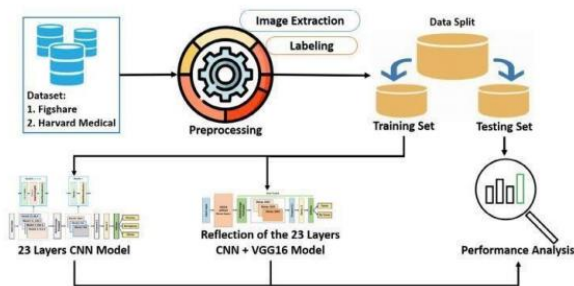


Figure 1. Proposed Block Diagram

A ConvNet is able to successfully capture the spatial and temporal dependencies in an image through the application of relevant filters. The architecture performs a better fitting to the image dataset due to the reduction in the number of parameters involved and reusability of weights. In other words, the network can be trained to understand the sophistication of the image better. The role of the ConvNet is to reduce the images into a form which is easier to process, without losing features which are critical for getting a good prediction. For this step we need to import Keras and other packages that we’re going to use in building the CNN.

23-layers CNN architecture:

The below figure 2 demonstrates the “23-layers CNN” architecture used to classify different tumor types, including meningioma, glioma, and pituitary. In the proposed architecture, we take MRI slices as input, process the slices in different layers, and differentiate them from one another. In this study, a total of 23 layers are used to process the slice. Below is the description of each layer: One of the predominant building blocks of the CNN model is the convolutional layer. It is a mathematical method that performs a dot product between two matrices to construct a transformed feature map. One matrix relates to the kernel, while the other presents the pixel intensity values of the original image. The kernel is used to move vertically and horizontally over the original image to extract properties such as borders, corners, shapes, etc. When we move further into the model, it begins to find more better features like blurring, sharpening, texturing, and gradients direction. A total of four convolutional layers with different kernel sizes, including 22*22, 11*11, 7*7, and 3*3, are included in the “23-layers CNN” architecture. We move the filter 2 pixels at a time using stride two over the input matrix. The convolution operation on image is shown in figure 3. The below figure 4 illustrates the max-pooling procedures where the feature map is in 4*4 blocks. As shown in this figure, max-pooling generates the most dominant features in every 2 * 2 blocks.

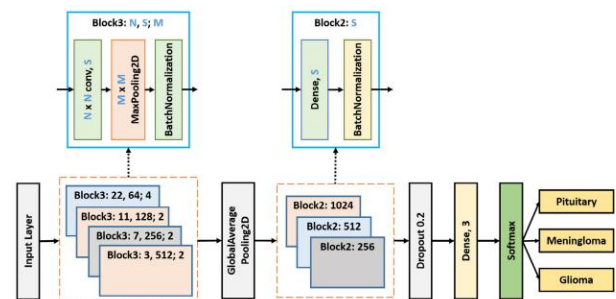


Figure 2. 23- Layers CNN Architecture

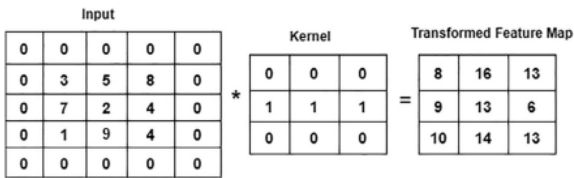


Figure 3. Convolution operation on image

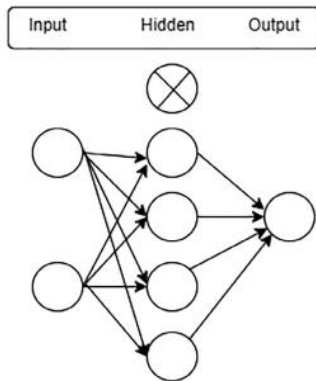


Figure 4. Max pooling Procedure

Batch normalization also plays a vital role in designing an accurate CNN model. It is used to regulate the model and enables a higher learning rate. It also helps to re-scale all the data to normalize the input data.

FLOW DIAGRAM

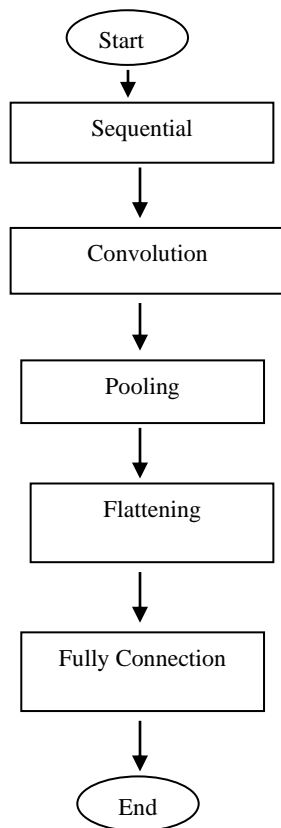


Figure 5. Flow Diagram

1.Start:

The process begins with the start symbol for initialising the neural network.

2.Sequential

To initialize the neural network, we create an object of the Sequential class.

```
Classifier = Sequential ()
```

3.Convolution

To add the convolution layer, we call the add function with the classifier object and pass in Convolution2D with parameters. The first argument feature_detectors which is the number of feature detectors that we want to create. The second and third parameters are dimensions of the feature detector matrix.

```
classifier.add (Convolution2D (256, 3, 3, input_shape = (256, 256, 3), activation='relu'))
```

4.Pooling

The Pooling layer is responsible for reducing the spatial size of the convolved feature. This is to decrease the computational power required to process the data through dimensionality reduction.

```
classifier.add (MaxPooling2D (pool size=(2,2)))
```

5.Flattening

The Flatten function flattens all the feature maps into a single long column.

```
classifier.add (Flatten ())
```

6.Fully Connection

The next step is to use the vector we obtained above as the input for the neural network by using the Dense function in Keras . The first parameter is output which is the number of nodes in the hidden layer.

```
classifier.add (Dense (output = 64))
classifier.add(Dense(output=1,activation='sigmoid'))
```

V. RESULTS AND DISCUSSIONS

The results are obtained by python language. Python is an interpreter, high-level, general purpose programming language created by Guido Van Rossum and first released in 1991, Python's design philosophy

emphasizes code Readability with its notable use of significant Whitespace. Its language constructs and object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects. Python is dynamically typed and garbage collected. It supports multiple programming paradigms, including procedural, object-oriented, and functional programming.

PIP: It is the package management system used to install and manage software packages written in Python.

Tensor Flow: Tensor flow is a free and open-source software library for dataflow and differentiable programming across a range of tasks. It is a symbolic math library, and is also used for machine learning applications such as neural networks.

Keras: Keras is an open-source neural-network library written in Python. It is capable of running on top of TensorFlow, Microsoft Cognitive Toolkit, R, Theano, or Plaid ML. Designed to enable fast experimentation with deep neural networks, it focuses on being user-friendly, modular, and extensible. Keras contains numerous implementations of commonly used neural-network building blocks such as layers, objectives, activation functions, optimizers, and a host of tools to make working with image and text data easier to simplify the coding necessary for writing deep neural network code. The figure 6 is applied as the input image.

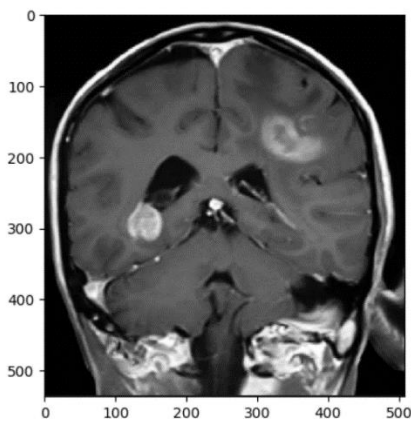


Figure 6. Input image

The output image obtained as shown in below figure 7. The graphs obtained by applying the proposed method are shown in below figures 8 and 9.

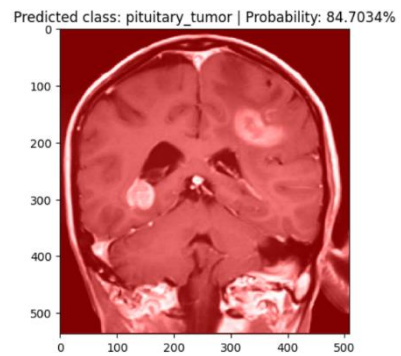


Figure 7. Output image

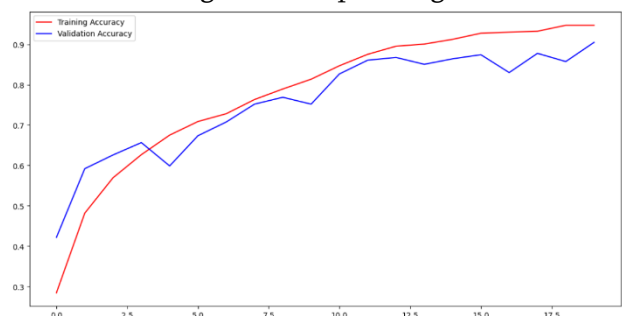


Figure 8. Graph 1

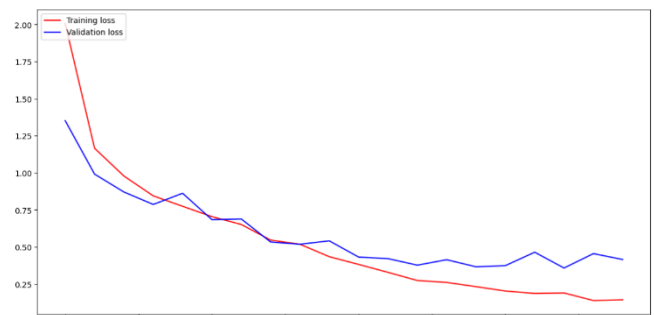


Figure 9. Graph 2

VI. CONCLUSION AND FUTURE SCOPE

In conclusion, our investigation into Brain Tumor Segmentation using Convolutional Neural Network (CNN) in MR Images has been surveyed. The methods and their results have been studied for brain tumor segmentation using CNN. The preliminary results showcase improved Accuracy and Validation. It sets the stage for further analysis and refinement as

VII. FUTURE SCOPE

The future scope of brain tumor detection using Convolutional Neural Networks (CNNs) is vast and holds immense potential for advancements in medical imaging and diagnosis. Some key areas of future exploration and development include:

Improvement in Accuracy: Continual efforts will focus on enhancing the accuracy of CNN-based brain tumor detection systems. This involves refining CNN architectures, optimizing hyperparameters, and incorporating advanced feature extraction techniques to achieve higher precision and recall rates.

Multimodal Imaging Integration: Integration of multiple imaging modalities such as MRI, CT, PET, and functional MRI (fMRI) can provide complementary information for more comprehensive tumor characterization. Future research may explore CNN models capable of effectively leveraging multimodal imaging data for improved tumor detection and classification.

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IX. 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”, Hindawi

International Journal of Biomedical Imaging volume 2017.

2. Andras Jakab, Stefan Bauer et al., “The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS) “IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 34, NO. 10, 2015.
3. Israel D. Gebru, Xavier Alameda-Pineda, Florence Forbes and Radu Horaud, “EM Algorithms for Weighted-Data Clustering with Application to Audio-Visual Scene Analysis “ IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. XX, NO. Y, 2016.
4. Prateek Katiyar, Mathew R. Divine et al., “A Novel Unsupervised Segmentation Approach Quantifies Tumor Tissue Populations Using Multiparametric MRI: First Results with Histological Validation” Mol Imaging Biol 19:391Y397 DOI: 10.1007/s11307-016-1009-y , 2016.
5. Zeynettin Akkus, Alfiya Galimzianova, Assaf Hoogi , Daniel L. Rubin and Bradley J. Erickson, “Deep Learning for Brain MRI Segmentation: State of the Art and Future Directions” J Digit Imaging DOI 10.1007/s10278-017- 9983-4, 2017.
6. Anupurba Nandi, “Detection of human brain tumour using MRI image segmentation and morphological operators” IEEE International Conference on Computer Graphics, Vision and Information Security (CGVIS), 2015.
7. Swapnil R. Telrandhe, Amit Pimpalkar and Ankita Kendhe, “Detection of Brain Tumor from MRI images by using Segmentation &SVM” World Conference on Futuristic Trends in Research and Innovation for Social Welfare (WCFTTR’16), 2016.
8. Komal Sharma, Akwinder Kaur and Shruti Gujral, “Brain Tumor Detection based on Machine Learning Algorithms“ International Journal of Computer Applications (0975 – 8887) Volume 103 – No.1, 2014.

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