Brain Tumor Detection

Namrata Lokhande[1] , Divya Chaudhari[2] , Diksha Kalasait[3]
Vishal Sonavane[4] , Bhondave S. D[5]
[1234]Student, ATC, SPPU, PUNE [5]Assistant Professor, ATC, SPPU, PUNE,
Maharashtra, INDIA

Abstract:- One of the most important and most difficult tasks in medical imaging is the segmentation of brain tumors because human classification of books can lead to errors and diagnostic errors. Specifically, this study uses MRI images to identify brain tumors. A brain biopsy is not usually done before brain surgery and is used to isolate brain tumors. Technology and machine learning could help radiologists make tumors without using invasive procedures. There are two types of brain tumors: benign and malignant. The quality of life and life expectancy of these patients improves with early and timely disease detection and treatment planning. Convolutional neural network (CNN) is a machine learning technique that is incredibly successful in image segmentation and classification. We describe a new CNN architecture to classify three types of brain diseases. The created network is smaller than the existing pre-trained network.

Keywords:- *Brain tumor, Magnetic resonance imaging, Adaptive Bilateral Filter, Convolution Neural Network. Introduction.*

I. INTRODUCTION

This work includes a system that uses a computer-based service to detect tumors and a neural network algorithm to classify tumors in MRI images of different patients. Various types of image processing, such as image segmentation, image enhancement and extraction, are used for brain diagnosis in MRI images of cancer patients. There are four steps to using image processing techniques to identify brain tumors: image preprocessing, image segmentation, feature extraction, and classification. Image processing and neural network techniques are used to improve the detection and classification of brain tumors in MRI images.

II. MOTIVATION

The main motivation behind brain tumor research is not only to detect the tumor, but also to show the tumor. So it is important in cases where we need to determine whether the tumor is good or bad, it sees the tumor from the image and returns the result whether the tumor is good or bad. This work includes a system that uses a computer-based service to detect tumors and a neural network algorithm to classify tumors in MRI images of different patients.

III. PROBLEM STATEMENT

Automatic brain recognition and classification are the main focus of our research. MRI and CT scans are often used to study the anatomy of the brain. Brain tumor diagnosis on MR images is the main purpose of this article. The main purpose of the mental health examination is to support the diagnosis. The aim is to combine various techniques to develop an algorithm that will guarantee the presence of tumors, thereby creating a reliable method of tumor detection in MR images of the nervous system. Techniques used include filtering, erosion, dilatation, thresholding, and tumor shaping techniques (eg, edge detection). Images are created during treatment; Manual segmentation of tumors or lesions is a complex, time-consuming task. Check for brain tumors or tumors.

IV. LITERATURE REVIEW

Segmenting a region of interest from an object is one of the most difficult and time-consuming tasks, and segmenting tumors from MRI brain images is an ambitious task. Researchers from all over the world are working in this field to achieve the ROI of the proposed segmentation and to simulate many different types of different angles. Neural network-based segmentation is now incredibly effective and the use of this method is increasing day by day. To complete the calculation, Devkota et al. A segmentation method based on the mathematical morphological and spatial FCM algorithm was developed. However, the solution has not been evaluated yet, and an accuracy rate of 86.6% has been achieved in results such as cancer diagnosis and classification. Yan Tao et al. Histogram segmentation method was used. Consider the challenge of brain tumors as a three-class classification problem using both FLAIR and T1 patterns, including tumor necrosis and tumor, edema, and tissue normal nose. Abnormal regions were identified using the FLAIR modality and region-based contour models. Using the K-means method and the contrast-enhanced T1 modality, the Dice coefficient was 73.6% and 90.3% sensitive, and edema and tumor were distinguished in abnormal areas.

V. METHODOLOGY

Image Archive: There are three types of tumors: menin giomas, gliomas, and pituitary tumors. Some patient images are obtained in three different planes: sagittal, axial and coro nal. Examples of different tumor types and morphological pl anes. The number of images obtained from each patient vari es. MR images of Image Preprocessing and Data Augmentat ion files are in int16 format and are in multiple sizes.

These images are normalized to represent the input layer of the network and scaled to 256256 pixels. We made two adjustments anyway to expand the data. The first change changes the view 90 degrees. Vertical image flip is the second change. This way we add three times to our dataset and make several images.

VI. CNN OPTIMIZATION

Machine **Learning** includes **Convolutional Neural Networks,** also known as convnets or CNNs. It is a **set** of various neural network models for different purposes and different data. CNN is a special type of **network of** deep learning **algorithms** designed for tasks such as image recognition and pixel data processing. Although there are many types of neural networks in deep learning, CNN is the **preferred** network architecture for recognition and **authentication.** Therefore, they are ideal for applications where computer vision (CV) performance and object recognition are **critical,** such as **human** faces and **vehicle traffic.**

Number of **convolutional neural network layers:**
1. 2D Convolution
MAX Poolig2D 2. a
3. **Reduce**
4. Flatten
5.Dense
6. **Remove Enhancement** and 2D Convolution **Features** from viewport.

Display results in matrix format.
MAX Poolig2D:
MAX 2D **selection, using** the largest in the **calibration** map
Dropout: Dropout is the practice of ignoring selected neurons during training.
Flatten: Feed output to all layers.
There is a list of documents.

Intensive: An environment where all inputs and **outputs** are **weighted together.** Next is the nonlinear activation function. **Open** the **approximate** probability of 0 and **1 using the**

Sigmoid function.
Since there are two **groups** (0 and), we use binary **cross entropy** in the compilation model.
We also use Adam **optimizer.**

Estimated time of Adam's **conversion.** It is used to **solve simple** non-convex optimization problems.

The calculation is valid. **There**
quires a small amount of memory to run **the**
Design Software The
collects MRI data from **multiple** sources **as a** first step.

Step 2: Prepare and **clean the** MRI data.
Step 3: Brain **Segmentation** using MRI **Image Segmentation.**
Extracting features from the segmented brain tissue is the fourth step.
Step 5: Train the CNN model using object extraction.
Step 6: Use the validation process on MRI scans to evaluate the software's accuracy and functionality.
Step 7: **Deploying** the software for **actual** use is the seventh step.

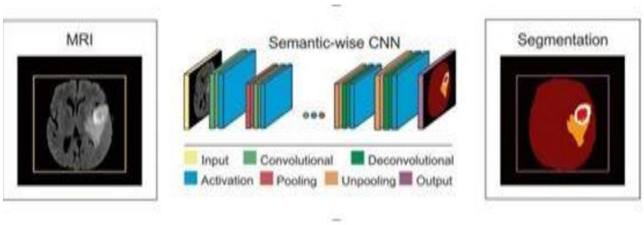

FIG 1: CONVOLUTIONAL NEURAL NETWORKS FOR BRAIN TUMOUR SEGMENTATION

Different Models	Accuracy (%)
Seetha et al.	97.50
Tonmoy Hossain et al.	97.87
Our CNN model	91.74

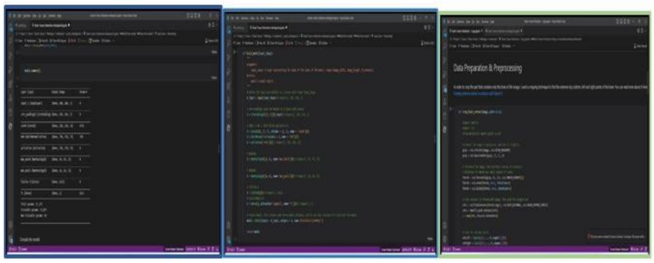

FIG 2: **DATA PREPARATION AND PREPROCESSING**

VII. CONCLUSION

The main goal of this research project is to create a brain part of the brain with high performance, accuracy, and flexibility. For modern brain tumors, using Fuzzy C-Means (FCM) as segmentation, tissue and image extraction, and SVM and DNN as classification. It's a little difficult. However, the calculations take a long time and are not very accurate. The proposed method includes a convolutional neural network-based classification for improved accuracy and faster computation. Also, results are classified as brain tumors or normal images. A deep learning method that uses feed-forward techniques is CNN. Also, Python is used for implementation. Web image databases are used for distribution. It belongs to the group of educational models. Therefore, training is only the best technique. In addition, depth, width, and height values and raw pixel values were taken from CNN. Use gradient descent. Calculate training accuracy, efficiency, and inefficiency. Correct education is 97.5% Again, accuracy is high and loss of evidence is low. Tumors can be visualized using CNNs. CNNs are useful for automatic feature selection in medical images. Doctors save images stored on the web and then separate test tumors into two groups, normal and diseased. A total of 226 images were selected as test data and a total of 1666 images were selected as training data. There are two sets of images divided by the ratio of patients to healthy participants. Images are preprocessed before being fed to CNN. Other classifiers such as the RBF classifier and decision tree classification have been used in CNN design to evaluate the performance of CNNs. CNN accuracy is measured at 98 with SoftMax.67% classification is correct. In addition, the CNN accuracy of the DT classifier and RBF classifier are 94.24% and 97.34%, respectively. In addition to model accuracy, we evaluate network performance using standard metrics for sensitivity, specificity, and accuracy. As a result, the CNN classifier with the best accuracy is the SoftMax classifier. Limited to three of 226 images, CNN can identify 98.67% of normal and infected images. Apply the recommended filtering technique to CNNs. Compared to traditional CNN, the treatment plan is 99.12% of test data. The accuracy of the doctor's diagnosis helps identify tumors and treat patients, ensuring the accuracy of treatment options.

REFERENCES

[1]. A. Sivaramakrishnan And Dr.M.Karnan "A Novel Based Approach For Extraction Of Brain Tumor In MRI Images Using Soft Computing Techniques," International Journal Of Advanced Research In Computer And Communication Engineering, Vol. 2, Issue 4, April 2013.

[2]. Asra Aslam, Ekram Khan, M.M. Sufyan Beg, Improved Edge Detection Algorithm for Brain Tumor Segmentation, Procedia Computer Science, Volume 58,2015, Pp 430-437, ISSN 1877-0509.

[3]. B.Sathya and R.Manavalan, Image Segmentation by Clustering Methods: Performance Analysis, International Journal of Computer Applications (0975 – 8887) Volume 29– No.11, September 2011.

[4]. Devkota, B. & Alsadoon, Abeer & Prasad, P.W.C. & Singh, A.K. & Elchouemi, A.. (2018). Image Segmentation for Early Stage Brain Tumor Detection using Mathematical Morphological Reconstruction. Procedia Computer Science. 125. 115- 123. 10.1016/j.procs.2017.12.017.

[5]. K. Sudharani, T. C. Sarma and K. Satya Rasad, "Intelligent Brain Tumor lesion classification and identification from MRI images using k-NN technique," 2015 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT), Kumaracoil, 2015, pp. 777-780. DOI: 10.1109/ICCICCT.2015.7475384