

# Brain Tumour Detection using Deep Learning

Rohit Chahal

BTECH CSE

GALGOTIAS UNIVERSITY, GAUTAMBUDH NAGAR,

GR. NOIDA, INDIA, PIN-CODE:-201310

rchahal756@gmail.com

**Abstract-** The fragmentation of human-assisted manual categories can lead to inaccurate predictions and diagnoses, so classification of the brain tumor is one of the most important and difficult challenges in the field of medical imaging. Moreover, if there is big data that should be national, it is a frustrating task. Because tumors in the brain have a wide range of appearance and because normal tissue and tissue are very similar, it is difficult to distinguish tumor regions from images. We suggested how to remove brain tumor from 2D magnetic resonance brain imaging (MRI) using the Fuzzy C-Means clustering algorithm, followed by classification classification and convolutional emotional networks in this study. Tests were performed on real-time databases with tumors of various sizes, locations, forms, and firmness. In the traditional classification category, we used six classical dividers used in scikit-learn: Vector Support Machine (SVM), K-Nearest Neighborhood (KNN), Multilayer Perceptron (MLP), Logistic Retreat, Naive Bayes, and -Random Forest. After that, we moved on to Convolutional Neural Networks (CNNs), which were built using Keras and Tensorflow and produced much better results than the ancient neural networks. CNN achieved a 97.87 percent accuracy rate in our study, which is surprising. The main purpose of this study was to use textual and mathematical knowledge to discriminate between normal and aberrant pixels.

## I. INTRODUCTION

Medical imaging refers to a variety of procedures that can be used to view within the body without being invasive [1]. Medical imaging entails a variety of image modalities and procedures used to scan the human body for treatment and diagnostic purposes, and thus plays a critical part in determining how to improve people's health. Image segmentation is a key and necessary stage in image processing that affects whether or not a higher level of image processing will be successful. In medical image processing, the major goals of picture segmentation are tumour or lesion detection, efficient machine vision, and obtaining a good result for further diagnostics. With the use of Computer Aided Diagnostic (CAD) systems, improving the sensitivity and specificity of tumour or lesion has become a key concern in medical pictures.

According to the American Cancer Society, brain and other nervous system cancer is the 10<sup>th</sup> largest. Cause of death, with a five-year survival rate of 34 percent for men and 36 percent for women. In addition, the world health organization (who) estimates that 400,000 people worldwide suffer from brain tumors, with 120,000 deaths in recent years. In addition, in the united states by 2019, an estimated 86,970 new cases of malignant and malignant brain and other central nervous system (cns) tumors are predictable. When abnormal cells are in the brain, a tumour appears with laboratory tests, mits look at one of the most common medical tests (blood and sample tests). with the rapid development of more sophisticated, less intrusive technology over the past decade, medical imaging has evolved. mits can be used to gain a better understanding of neuroscience and human behavior.

figure 1 shows the basic concept of a medical thinking system, which contains a sensory or energy source that can enter the human body. as energy passes through the body, it is absorbed or reduced to varying degrees, depending on the density and atomic number of different tissues, leading to signals. special sensors associated with the power source receive these signals, which are then mathematically altered to form an image. images obtained by force emanate from the human muscle, leading to a division based on the energy used in the body.

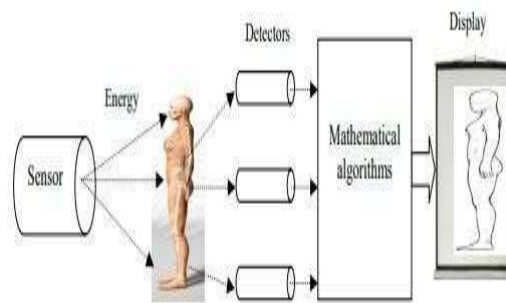


Fig 1. Concept of a medical imaging system

Many different methods can be used to look inside a patient, depending on the sources of energy. These methods work by sending a signal directly to the patient. These symptoms interact with the patient's tissues. An internal image of a patient can be created by receiving a signal from the body. X-ray radiography, X-ray Computed Tomography (CT), Magnetic Resonance

Imaging (MRI), ultrasonography, elastography, optical imaging, radionuclide imaging (Scintigraphy, Positron Emission Tomography (PET) ), and Single Photon . A tumour is a rare tissue which can be spread in all the cells of the brain. Emission Computed Tomography (SPECT), thermography, and terahertz imaging are available some of the strategies discussed in this paper. As of 2010, more than 5 billion medical imaging studies have been performed worldwide.

An X-ray discovery by Röntgen in 1895 marked the beginning of radiography. When Röntgen looked at his wife's handwriting on an X-ray image, he realized that it could be used for medical purposes. Cormack first described CT as a photographic technology in 1963. The first clinical CT scan was launched in Hounsfield in 1972. Since then, clinical X-ray has changed the medical image and is often regarded as one of the most important innovations in radiology since its discovery. For X-ray. For non-invasive brain tumors, computer-assisted access (CAD) is the preferred method. Magnetic Resonance Imaging (MRI) is used to capture images of the brain, which are prone to noise and deviations such as labeling and intensity changes during detection. In addition to the tumor, the brain image contains many other structures such as cerebrospinal fluid, gray matter, white matter, and skull tissue. A tumor on the brain is a rare tissue caused by uncontrolled cell growth that has become one of the most serious diseases affecting human health.

Therefore, how clinical trials are used in surgical planning and radiotherapy is important in the evaluation diagnosis of brain tumor. Because of its distinct imaging techniques, such as non-abrasive, non-abrasive, and high-viscosity of soft tissue, the analysis of magnetic resonance-based medical imaging (MRI) has attracted much attention in the past year with human research. the brain.

The main purpose of brain image imaging is to extract important clinical information about the patient and diagnostic features of MRI, which are needed for diagnostic purposes including tissue volume analysis, diagnosis and injury, and surgical planning. As a result, spontaneous and accurate brain classification is important. However, categorizing brain tumors from MRI data is one of the most difficult problems in analyzing a medical image due to their unpredictable appearance and shape, as well as inter- and intra-rater variability. the use of image processing as digital photography suffers from a variety of problems such as the lighting problem mentioned above and therefore without proper image processing techniques, even CNN can find fault in learning the wrong features and producing negative results. We also need to choose the right techniques because the biggest problem with processing images in databases is that the chosen method may be beneficial.

## II. LITERATURE SURVEY

medical imaging techniques (mits) are rare ways of seeing the body without opening it physically. it was once used to help diagnose or treat various ailments. there are many medical imaging procedures, each with its own set of risks and benefits. this paper provides an overview of various strategies, including their concepts, benefits, barriers, and their application. x-ray radiography, x-ray computed tomography (ct), magnetic resonance imaging (mri), ultrasonography, elastography, optical imaging, radionuclide imaging (scintigraphy, positron emission tomography (pet), and single photon emission computed tomography (spect), thermography, and terahertz imaging are among the areas to be concerned about. in detail. comparisons of various techniques will be presented in terms of image quality (local resolution and brightness), safety (effects of ionizing radiation on the body, and temperature effect of radiation on the body), and system availability (real-time information and cost).

Using Mathematical Morphological Reconstruction, this work proposes a computer-assisted diagnostic technique to diagnose brain tumors in their early stages (MMR). The image is processed in advance to remove noise and artifacts before being classified to determine regions of interest such as vegetation. To determine whether the brain tumor in a photograph is malignant or benign, a large number of textual and mathematical features are returned to the framed image.

Testing shows that different images have a good level of accuracy while cutting computer time significantly. Studies show that the proposed treatment has a high degree of success in diagnosing brain tumors in patients. Because of the unpredictable appearance of tumor tissue in actual function, dissecting a brain tumor using magnetic resonance imaging is a difficult and time-consuming task. We present a novel model based on the novel distinction of plant extraction from multi-modality magnetic resonance imaging in this work. We form the pixel-level tumor into three categories: tumor, edema, and healthy tissue.

First, we use a region-based working model in T2-weighted images with reduced fluid retrieval mechanisms to detect deviant circuits, and then use a different level setting to measure image intensity on both sides of the component. Separating the interested region into an object is one of the most difficult and time-consuming tasks, and isolating a tumor on the MRI Brain image is a big deal. Researchers from all over the world are working on this topic to find the best-distributed ROI and mimic many different approaches with different perspectives. Today, Neural Network-based segregation produces excellent results, and the use of this model is growing day by day.

Devkota et al. a whole classification process has been developed based on Mathematical Morphological Operations and the local FCM algorithm, which reduces

calculation time. However, the proposed solution has not been tested until the testing phase, and the results are as follows next: detects cancer with 92 percent accuracy and the divider has 86.6 percent accuracy. Yantao et al. he used a technique similar to the histogram-based segmentation technique. About the challenge of brain tumor classification as a problem of three classification (tumor, necrosis, tumor, edema, and normal tissue) in two ways FLAIR and T1. The region-based contour model for FLAIR modality has been used to detect deviant regions. The k-means method was used to differentiate edema and tumor tissue in untreated areas using the T1 method to improve differentiation, with a Dice coefficient and sensitivity of 73.6 percent and 90.3 percent, respectively. Badran et al. [9] used the canny edge and adaptive thresholding detection model to generate ROI using the edge detection methods.

In the future, the development of the proposed algorithm could be done by working with limits, output quality images can be enhanced using better morphological jobs the proposed method for that brain MRI scan removed noise uses DWT by accessing wavelet efficiency. Inheritance. An algorithm is used to detect a plant pixels. You are genetically modified An algorithm is then used to determine the best a combination of information released by the nominees matter. The current method uses k-Means clustering methods in Genetic Algorithms to guide this latter Evolutionary Algorithm in his search to find the best or very little data fragmentation. This method has been achieved phase accuracy from 82 percent to 97 percent of they found plant pixels based on basic facts. Limit of this function that the conversion of the wavelet requires large storage and its calculation costs are high.

Dangerous brain tumours (e.g. glioblastoma) are other lethal neoplasms with high heterogeneity and mortality. Brain barrier (BBB) inhibits the entry of macromolecules (100%) and small molecules (> 95%, e.g. anti tumour drugs) into the brain. In the addition, brain tumours have unique growth, progression, and metastasis characteristics that are influenced by multiple drug resistance mechanisms. The aggressive and aggressive nature of brain tumours is a major reason for failure to diagnose, resulting in a 5-year survival rate of 35%. Patients with brain tumours often recur- despite general treatments.

### III.METHODOLOGY USED

The proposed model system prompts the user to choose:

1. Create and train model.
2. Record and identify the disorder.
3. Predict disorder on a specified file.

The input data set is usually composed of a small data set consisting of 3762 plant images and a small set containing 2297 images. The selection of the subset set was made based on the removal of images that may have been

misleading model training. Another small database of 253 images has been added. This database contains 155 plant images and 93 non-plant images. For some non-vegetative images, all 105 non tumour images from another dataset were used. The non-vegetarian image folder is named "no\_tumor" in the original database in Kaggle. Images were pre processed and then a 70% -30% split for training and verification data. Preliminary analyzes used included histogram measurements followed by openings. The resulting data set was sampled to obtain a final database of 4222 images comprising 1861 training plant images, 563 non-training plant images, 1463 image validation images, and 315 non-training plant images. The upsampling is done as the database should be large enough for the model.

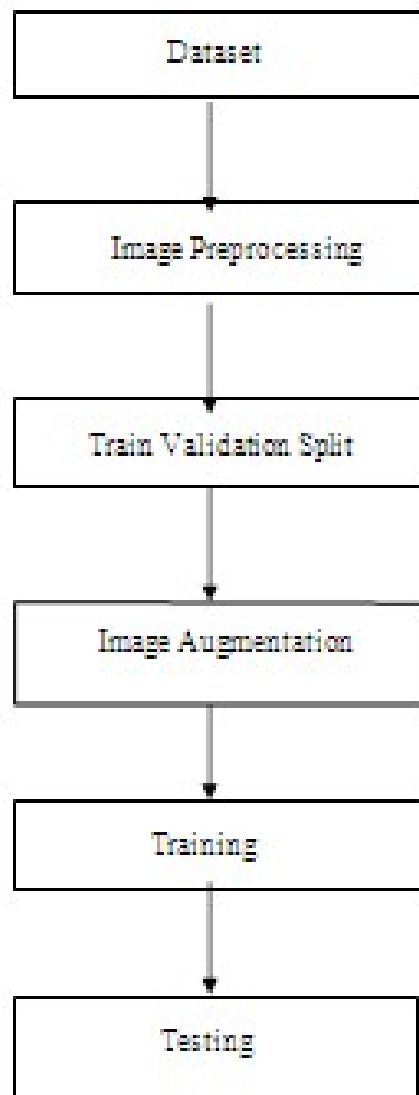


Fig 2. Proposed Algorithm

## Data set

**Image preprocessing:** This is used to improve image quality so that we can better analyze it. With some advance processing we can suppress unwanted distortions and improve certain features needed for the particular application we are working on. Those features may vary for different applications. And we get more clear images of the brai and can identify the image properly what's the problem actually have in a brain.

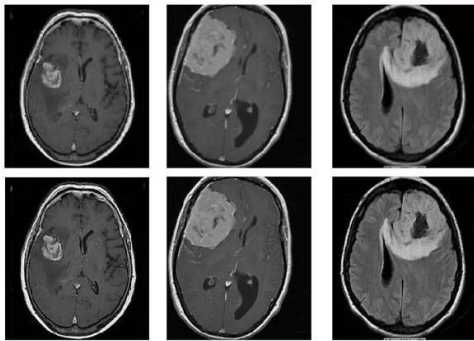


Fig 3. Pre processing brain images with brain tumour onMR images

**Train Validation Split** Train-Valid-Test segmentation is a way to test the performance of your machine learning model - segmentation or deceleration.

**Image Augmentation** Image enhancement is the growth that takes place in the image database using specific transitions such as rotation, horizontal scrolling, etc. The need to enlarge the image arises when existing data is insufficient in the sensory networks or when there is a development of scope on the neural. net performance if additional data is provided. So enlargement increases the size of the database. It also prevents the neural network from memorizing data by adding local variation to images, thus preventing excessive corrosion. Tensor Flow Image Data Generator generates an image generator that can be uploaded to a neural network for training and testing purposes. The need to add here is due to the fact that neural networks improve when data sets are larger and since our database contains 4222 images, we should expand. We can create many variations of the image. Think of a picture of a cat, if you show it from left to right or up and down, it still lives like a cat. If we go around the picture, then again we are always a cat. We can create such variations in person and store them in a database but in doing so, we will need more memory and time. Image Data Generator creates such variations internally thus it takes less time and does not take up much memory. Augmentation used:

1. All images are resized to 150x150 pixels.
2. Rotate the image between -30 degree and +30 degree.
3. Horizontal shift by 20% of image width to left or right.

4. Changing the shape by 20% of the image length up or down.
5. Shear - Clean the image according to the axis.
6. Zoom in 20%
7. Apply horizontal scrolling to photo

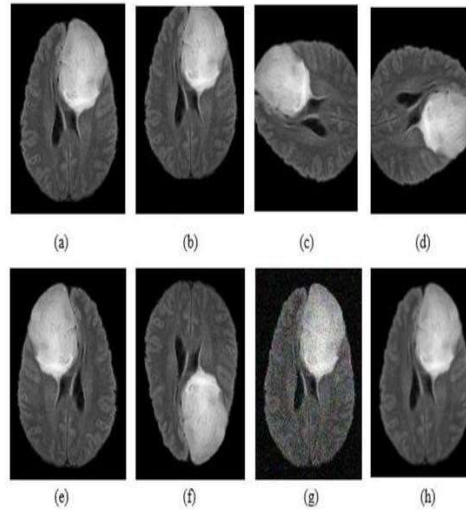


Fig 4. Brain tumour augmentation.

## Training

We have used the convolutional neural network as our model as CNNs are neural networks that are best suited to images. Transfer learning [15] has been used which means that the training to be done by our neural network will be based on a pre-trained network. We have used a previously trained model that has learned many complex aspects. The pre-trained ResNet101 v2 model will be our basic model on which we will streamline our work to distinguish both plant and non-plant images. Reason for using ResNet: In the case of common neural networks, an increase in the number of layers will reduce the error to a certain point but will begin to increase again.

These additional layers should not interfere with training for the resolution to be delivered to ResNet. ResNet uses an escape link where the output of the previous layers will affect not only the next layer but also the layers before it. Using Regularization can eliminate the side effects of additional layers. At the top of ResNet, a flat layer was used to lay out the output matrix of the previous layer into identical members. A tight layer for extra training and to avoid any overcrowding, use Dropout layer. Dropout layer drops nodes with a p probability of any over-reliance on output from certain nodes only is avoided. The p value used was 0.2. The activation function used was the Rectified Linear Unit (ReLU) and the use of sigmoid is in the final stage as it is a binary split system — yes or no problem.

#### IV.RESULTS

##### Classifiers

We can also conclude the performance of the classifiers using the below formulas

$$\text{Accuracy} = (TP+TN) / (TP+FP+TN+FN)$$

$$\text{Sensitivity(recall)} = TP / (TP+FN)$$

$$\text{Specificity} = TN / (TN+FP)$$

$$\text{Precision (PPV)} = TP / (TP+FP)$$

Table 1 for confusion metrics of classifiers

classifiers	accuracy	Recall	Specificity	Precision	Dice Score	Jaccard Index
k- nearest neighbour	89.39	0.949	0.482	0.933	0.941	0.889
Logistic Regression	87.88	0.949	0.286	0.918	0.933	0.875
Multilayer Perceptron	89.39	1.00	0	0.894	0.944	0.894
Naïve Bayes	78.79	0.797	0.714	0.959	0.870	0.770
Random Forest	89.39	0.983	0.164	0.903	0.943	0.892
SVM	92.42	0.983	0.428	0.935	0.959	0.921

We can see in Table that, of the six traditional machine class dividers, SVM produces the best results, with a accuracy of 92.42 percent. Although Naive Bayes provided excellent results in terms of accuracy and precision, the difference

between SVM and Naive Bayes was small and insignificant compared to other performance metrics. Some performance measures show that SVM has produced the best results according to the Jaccard Index, Dice Score, Precision, and Recall, among others.

We trained our CNN model and we recorded the performance

No.	Training Image	Testing Image	Splitting Ratio	Accuracy (%)
1	152	65	70:30	92.98
2	174	43	80:20	97.87

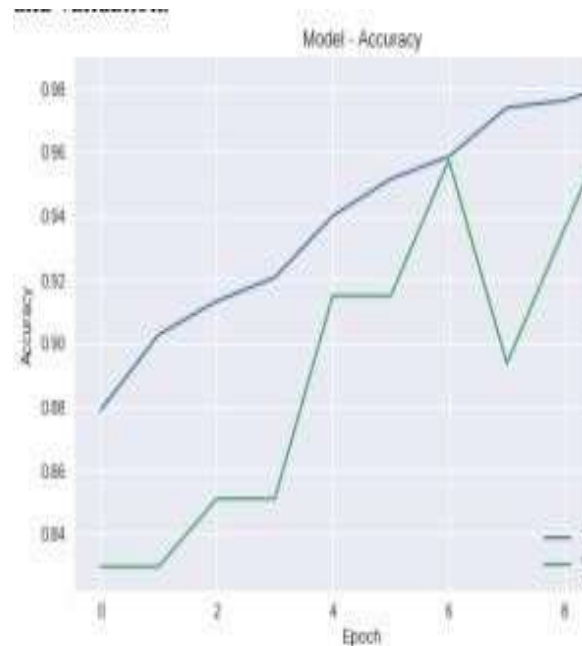


Fig 6 Accuracy of the proposed CNN model

#### Performance Comparison

Finally, we compared our proposed methods, which include classification of classical machine learning with CNN. We also compared our findings with those of other studies that used the same database. Researchers from Setha et al. achieved an 83.0 percent accuracy using SVM-based split and 97.5 percent using CNN. Both machine learning and segmentation based on CNN produced better results using our proposed method. Mariam et al. we havefound a 95% dice coefficient, while we have a 96% dice school.

Methodology	Accuracy (%)
Seetha et al[17]	97.5
Proposed CNNmodel	97.87

Through this tests we can identify correctly that the tumour is present or not and we can predict it wrongly or correctly.

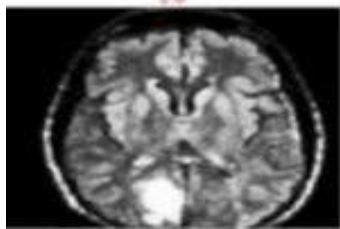


Fig 9 Wrongly predicted test image.

## V. CONCLUSION

Medical image processing is highly dependent on the classification of images as medical images are very different. We used MRI and CT scans to diagnose brain tumors. The most common use of MRI is to dissect and dissect the brain tumor. In classifying the tumor, we used Fuzzy C-Means clustering, which can accurately predict tumor cells. After classification, classification classification and Convolutional Neural Networks are used to classify data. We have used and compared the results of many traditional class dividers such as K- Nearest Neighbor, Logistic Regression, Multilayer

Perceptron, Naive Bayes, Random Forest, and Vector Support Machine in the standard division class. SVM had a high accuracy of 92.42 percent between these standard methods. In addition, we added CNN with improved results, resulting in 97.87 percent accuracy with an 80:20 split ratio in 217 images, i.e. 80 percent training images and 20 percent test images. We aim to work with 3D brain images in the future to find the most effective classification of brain tumor. Working with large databases will be extremely difficult in this regard, and we want to create an abstract database that emphasizes our country, which will help us expand the scope of our research.

## REFERENCE

[1] Kasban, Hany & El-bendary, Mohsen & Salama, Dina. (2015). "Comparative Study of Phototherapy Methods". International Journal of Information Science and Intelligent Programs. 4. 37- 58. J. Clerk Maxwell, Electricity and Magnetic Agreement, 3rd ed., Vol. 2. Oxford: Clarendon, 1892, pp. 68-73.

[2].D. Surya Prabha and J. Satheesh Kumar, "Assessment of Image Separation Performance Using Objective Methods", Indian Journal of Science and Technology, Vol 9 (8), February 2016.

[3].Brain Tumor: Statistics, Cancer.Net Editorial Board, 11/2017 (Accessed 17 January 2019)

[4].Kavitha Angamuthu Rajasekaran and Chellamuthu Chinna Gounder, Advanced Brain Tumor Distribution from MRI Images, 2018.

[5].General Information About Adult Psychiatric Plants ". NCI. 14 April 2014. Archived from the original 5 July 2014. Retrieved June 8, 2014. (Accessed 11 January 2019)

[6].M. Young, Technical Writer's Letter. Mill Valley, CA: University Science, 1989. B. Devkota, Abeer Alsadoon, P.W.C. Prasad, A.

[7]K. Singh, A. Elchemi, "Image Component of Early Phase Brain Acquisition using Morphological Mathematical Reconstruction," 6th International Conference on Smart Computing and Communications, ICSCC 2017, 7-8 December 2017, Kurukshetra, India .

[8] Niklas Donges (2019, June 16). What is transfer reading? Exploring the popular deep learning method. Builtin. <https://builtin.com/datascience/transfer-learning>.

[9] American Association of Neurological Surgeons. (n.d.). "Classification of Brain Plants". <https://www.aans.org/en/Media/Classifications-of-Brain-Tumors>

[10] Charles Patrick Davis. (2020, August 24). "How do you get Brain cancer?" [https://www.medicinenet.com/brain\\_cancer/article.htm](https://www.medicinenet.com/brain_cancer/article.htm)

[11] Vijayakumar, T. "Classification of Type Cancer by Mechanical Learning." Journal of Artificial Intelligence 1, no. 02 (2019): 105113.

[12] Pandian, A. Pasumpon. "Identification and classification of cancer cells using a capsule network with pathological images." Journal of Artificial Intelligence 1, no. 01 (2019): 37-44.