A Review on Brain Tumor Detection Using Convolutional Neural Network

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ABSTRACT

Background/Purpose: *The automatic identification of brain tumor types is important for advancing remedy and boosting survival of patients. In nowadays, magnetic resonance imaging is only used to effectively explore a variety of brain cancer. Since manual categorization of brain cancer requires experts and is only suitable restricted collection of clear MRI pictures, study of Convolutional Neural Network model for automatic diagnosis of brain tumor and how neural network technics are applied in images to detect tumor is proposed in this review paper.*
Design/Methodology/Approach: *Various Scholarly articles and websites are referred and studied to gather information for this review paper.*
Findings/Result: *Convolutional neural network and its different layers in image processing.*
Originality/Value: *This review-based research article is a brain tumor study detection implementing a Cnn Architecture as well as the research gaps and research Agenda.*
Paper type: *Literature Review*
Keywords: Brain Tumor , Convolutional neural network (CNN), Artificial Neural Network, ReLU, Pooling, Image processing, ABCD analysis.

1. INTRODUCTION :

A brain Tumor is the abnormal development of cells within the brain. Tumor s are categorized into two categories: benign and malignant [1]. It is further subdivided into primary and secondary components. Primary Tumor s start in the brain and spread to the rest of the body. Imaging tests help doctors decide whether the cancer is a primary cancerous Tumor or cancer that has spread to the brain from somewhere else in the cell. Although CT scans and EEGs are used to diagnose brain Tumor s, the most effective and widely used method is magnetic resonance imaging (MRI) [2-4]. MRI uses powerful magnetic fields and radio waves to create internal images of the body. Because magnetic resonance imaging provides more detailed information about internal organs. Artificial intelligence technology and machine learning have made significant advances in science and medicine in recent years, such as the Medical Computer Vision techniques, which allow the capability to detect serious conditions quickly, whereas previously it was tiresome and time-consuming. To overcome such drawbacks, software technology is critical, since this health sector is implementing quality and dependable methods to accurately identify life-threatening deadly diseases, which are the leading cause of death for patients worldwide. Brain Tumor segmentation is one of the most challenging and complicated tasks in computer vision because human-assisted manual categorization can result in incorrect diagnosis and prediction. Apart from that, it is a difficult process when there is a large volume of information to be filtered. Because brain Tumors have a wide range of images and share similarities with normal tissues, obtaining Tumor places from visuals becomes difficult [5-8]. In this study, we use brain MRI images to classify brain Tumor s as cancerous or non-cancerous using a deep learning technique and a CNN model.

2. RESEARCH OBJECTIVES :

The focus of this paper's research is on medical image processing using convolutional neural networks. The research's primary goal is high-accuracy diagnosis automation. Following are the few objectives developed for our research.

(1) To explain the benefits of automation in medical image diagnosis.
(2) To introduce the role of artificial neural networks in Image processing.
(3) To explain convolutional neural network and its different layers in image processing
(4) To understand Neural network Architecture
(5) To analyse different brain tumor segmentation approaches.
(6) To study artificial neural networks and convolutional neural networks.
(7) To evaluate the aspects of the system using ABCD analysis.
(8) To create the system framework.
(9) To identify research shortfalls and future directions in terms of contributing to continued study.

3. RESEARCH METHODS APPLIED :

The suggested study employs a methodological approach to conduct a literature review on the subject. This study's data was gathered from secondary sources such as journals, magazines, research papers, and books that are freely obtainable on the internet. A comparison was carried out, as well as the deficiencies of current systems were identified.

4. PROMINENT THEMES :

CNNs are used to map image data to an output variable. It is used for any type of prediction that uses image data as an input. The available literature is collected from Google Scholar on the articles published between years 2018 to 2021. Keyword 'Convolutional neural network'. Convolutional neural networks or CNN are a class of deep neural networks used in deep learning and machine learning. Details of the literature review are listed in Table 1.

Table 1: Literature study on Convolutional neural network

S. No.	Area of Study	Focus	Outcome	Reference
1.	CNN architecture	Framework, extinction-group, and space-group classifications	Crystal structure classification using a convolutional neural network	Park, et al., (2017). [9]
2.	Recent advances in CNN	Recent advances in improvising CNN	Pattern recognition layer design, activation function, loss function, regularisation, optimization, and fast computation have all improved.	Gu, et al., (2018). [10]
3.	Applications of CNN in radiology	Recent applications in radiology for image classification and segmentation	Study on CNN in radiology like classification of lung nodules on computed tomography.	Yamashita, et al., (2018). [11]
4.	Classifications with CNN	Classification using ANN and CNN	Convolutional neural networks are used to classify phonocardiograms.	Deperlioglu, et al. (2018). [12]
5.	Multitask CNN	Brain tumor detection	Model does multitask using automated network and also segmenting brain tumor	Rezaei, et al. (2018). [13]

6.	CNN Layers	Complex network classification with convolutional neural network	CNN for network classification problem. Validation of model through Empirical and synthetic data.	Xin, et al., (2020). [14]
7.	Medical image processing	Brain tumor detection using CNN	Accuracy of Sequential neural model is less than Convolutional neural network model	Totakura, et al., (2021). [15]

Image Processing refers to the act of converting a photograph to digital format and then performing various operations on it to extract useful data. Available literature is collected from Google Scholar on the articles published between years 2018 to 2022 with the keyword 'Image processing'. Table 2 contains the results of the literature review.

Table 2: Literature study on Image processing

S. N.	**Area of Study**	**Focus**	**Outcome**	**Reference**
1.	Challenges in Medical Image Processing	Image big data and medical Image management	Application of a graphical Processing unit for optimised algorithms and sophisticated parallel processing methods for sizable dataset.	Scholl, et al. (2011). [16]
2.	Medical Image processing in GPU	Image processing in a networked environment	For data parallel structure and high thread count, GPU processing is used in medical image processing techniques.	Smistad, et al. (2015). [17]
3.	Image processing with a deep convolutional neural network	Convolutional Neural networks used in Image processing	Different techniques of image processing like Image Reconstruction. Filtering with linear functions. Analysis of Independent Components Pixelation & matching templates.	Rawat, et al. (2017). [18]
4.	Medical Image processing Methods	Deep Learning methods fundamental concepts	Image registration, anatomical/cellular framework recognition, tissue categorization, computer-aided medical diagnostics, or prediction achievements. Interpolation methods in medical image processing	Shen, et al. (2017). [19]
5.	Applications of deep. learning in medical image processing	Machine learning algorithms to medical images processing	Image of an unusual axial input a design is run through a portion of an MRI brain image. A	Ker, et al. (2017). [20]

			CNN is featured performing a medical classification task. To extract, the Convolution, RELU, and pooling layers are employed. Before the fully classification, features from the input image are extracted layer that is linked.	
6.	Deep learning in medical imaging	Deep learning technique SVM	Clustering between two-point classes using support vectors	Razzak, et al. (2018). [21]
7.	Detection and recognition of images	Deep learning in medical image processing	Detecting blurriness in confocal scanning images automatically.	Maier, et al. (2019). [22]
8.	Image. segmentation	Image Semantic segmentation Networks. framework	Object classifier, detection, and segmentation are all combined in this multi-vision task. Creating a new loss function and fine-tuning the training. Using the transfer learning concept, and then validating it on the self-constructed indoor scene data set.	Huang, et al. (2020). [23]
9.	Medical Diagnosis image processing using CNN	Cellular Neural Networks to investigate Magnetic Resonance Imaging diagnostics	Image is generated is critical in assisting the surgeon in tumour removal using gamma knife radiosurgery.	Yu, et al. (2021). [24]
10.	DL-CNN-based Image processing methods are used in this approach.	Three image enhancement variations, Five-, seven-, and nine-layer CNN models	The disparity between training and validation has decreased. As the number of Convolution layers in models grows, so does the loss.	Tayal, et al. (2022). [25]
11.	Hybrid Machine Learning-Based CNN	Standard Medical event solvent extraction that acknowledges the mutual extraction Of two tumors even Attributes	Enhancement Of model relocation learning ability	Dhiman et al. (2022). [26]

Various brain Tumor detection techniques are discussed in this section. Research article published by Brindha, et al. (2021) [27], a work Artificial Neural Network (ANN) and Convolution. Neural Network (CNN) is applied in detecting the presence of brain tumors. It’s a study on CNN and how CNN makes

predictions by reducing the image size without losing the necessary information for the predictions. The model developed here is based on trial-and-error method.
Febrianto, et al. (2020) [28], have made a comparison between two brain tumor models for classification and finding the best model among two using CNN. Furthermore, more convolutional layers enhance the model's efficiency while increasing the time required to train the model.
Gupta, et al., (2013). [29], has studied about Artificial Neural Network Framework and its framework.
Benardos, et al., (2018). [30], shows the architecture of neural network. It's a study on proposing finest framework and is predicated on the use of a genetic algorithm (GA) and the development of novel performance measures for ANNs.
Wu, et al., (2018). [31], is a study on Activation functions in neural networks. It shows how ReLU activation function used in facial expression recognition.

3. AUTOMATION IN MEDICAL IMAGE DIAGNOSIS :

In Manual brain tumor segmentation, tumor cells detection is complicated with MRI image regions based on the Radiologists experience and subjective decision-making quality. As a result, fully automatic, unbiased, and observable segmentation methods are required [32].
The use of analytical modeling to quantify gliomas opens up a new border area in radiology. Radiologists must stay up to date on advances in artificial intelligence. Techniques that introduce analytics and machine learning will reward systems visual image interpretation. Anatomy categorization of regions of interest (ROI), for example, specifying a density of abnormal growth from a healthy tissue's viewpoint, is an important step in the image processing pipeline. This will enable data study of functionalities that are not noticeable to visual acuity. Radiomics, for example, is rapidly evolving as a method of trying to predict overall survival from visualising attributes like the contour of a field of view and the appearance and severity of the voxel habitat. As these methods advance, there will be a significantly larger necessity automated classification [33]. A convNet is a deep learning algorithm that can be used to detect and segment brain Tumor s in MRI images.

4. ARTIFICIAL NEURAL NETWORK IN IMAGE PROCESSING :

Biological Neural Networks, which contain the human cerebrum, usually catapult Artificial Neural Networks (ANN). An Artificial Neural Network is a network of nodes called Artificial Neurons, which are very similar to cells in the brain. A neural network is made up of sequential phases of nodes or neurons. A neuron is a function in a deep neural network that accumulates data and categorises it based on a specific pattern. When an artificial neuron receives a signal or data, it processes it and can flag or pass data to other neurons with which it is associated [34-37].
Image processing with neural nets (ANN) was used profitably in a wide range of activities, including interdisciplinary field, machine design, design process, manufacturing surveillance, cybersecurity, machinery, and transportation. Object pre-processing, pattern discovery, categorization, and pattern recognition are the processes used in image management with ANN [38-40]. A picture is commonly represented as a matrix, with each row of the matrix containing colour features after a pixel. The matrix is used as a source file to the CNN architecture. The tiny dimensions of the images quickly and easily aid in determining the dimensions of the vector and thus the number of input vectors. A sigmoidal function could be used as a transfer function [41].

5. CONVOLUTIONAL NEURAL NETWORK :

The Convolutional Neural Network. (CNN) is a deep neural network with many hidden layers. It is a deep network that mimics how the brain's visual cortex operations and identifies pictures. Image recognition is generally image classification. Recognizing whether the image of a picture is cancer or non-cancer is the same as categorising the image as cancer or non-cancer class [42-46]. An image is understood by a computer by assigning numbers to each pixel. CNN analyses images one by one. The sought-after parts are referred to as features. By locating irregular feature matches in two images that are in exactly the same place. In terms of detecting similarity, CNN outperforms the entire image matching scheme. These are merely slivers of a larger picture. The chosen feature is applied to the input image, and if it matches, the image is classified correctly. [47-51]. CNN is a technique that takes an image as input and adds values in the form of weight and bias to the various parts of the features in an image in order to distinguish between them. Computer reads the image as an array of pixel values ranging from 0 to 255 [52-54].

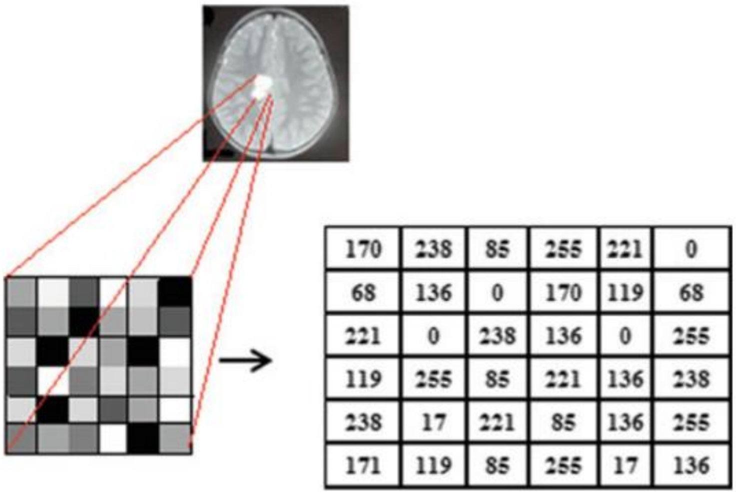

Fig. 1: Reading an Image in pixel ranging from 0-255

Convolutional networks perform a type of search by the product of two functions. Convolve means to convulse around each other. A CNN's network is a type of search Convnet is used for feature extraction and repeatedly scans over a digital object horizontally, vertically, and diagonally. This image detection is called image convolutions. A kernel is a number matrix used in image convolutions. Different kernel pattern sizes can produce more accurate, and kernel size is undefined, but 3x3 is used as the maximum. A kernel or filter is used to detect features [55].

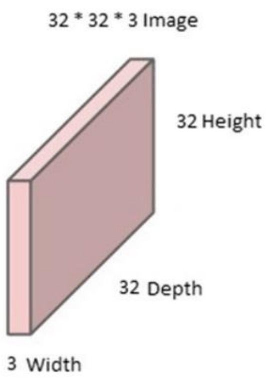

Fig. 2: Image of size 32×32×3

Figure 2 shows an input image of size 32 x 32 x 3 that contains the raw image pixels. This image has a width of 32, a height of 32, and 3 Rgb channels (red, green, blue).

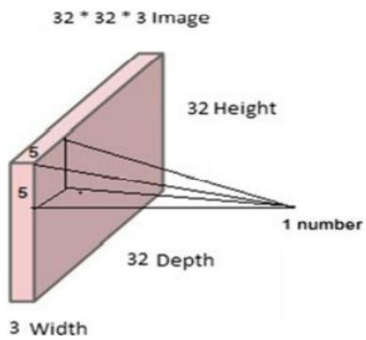

Fig. 3: Applying filters on 5x5x3 size of an image

The above (Fig. 3) Filter is used for feature detection. Shows the filtering on small part of an image of -size 5x5x3. Once the filter moves all over input image, it multiplies the attributes. The filter that uses the image's actual pixel values.

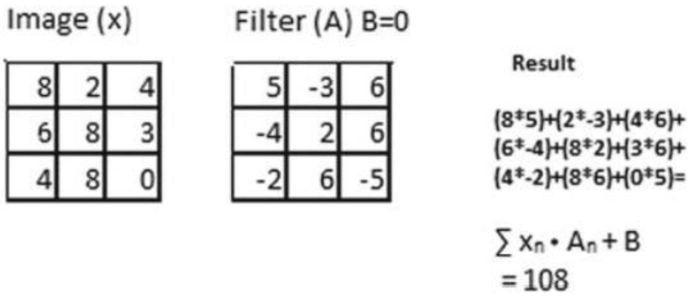

Fig. 4: Applying filters (dimension dot product + bias)

A convolutional network has many layers. The 3 main layers are:

I. Convolutional layer

II. Rectified Linear Unit

III. Pooling Layer

CONV layers:
Following are the steps in CONV layers.

(i) Compare the attribute and the image

(ii) multiplied by the corresponding feature pixel for every image pixel

(iii) Sum them all up

(iv) Divide by the total pixel values in the feature.

ConV layers calculates the neurons outputs which are connected to inputs [56-68]. Each output neurons are calculated by computing a dot product between their weights and a small region connected to the input values. This convolution is performed with every other features.

ReLU Layer:
This layer zeros off all negative values in the filtered image. To avoid the values totalling to 0, this is done [69].

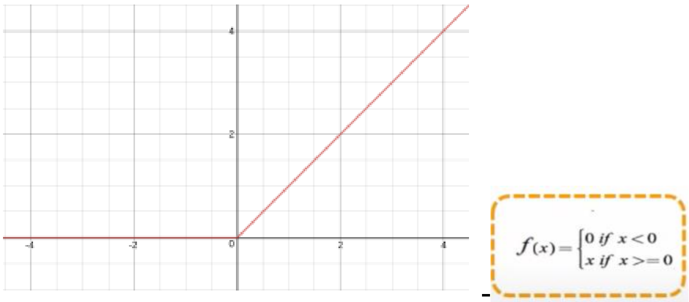

Fig. 5: Applying filters (dimension dot product + bias)

A Rectified linear activation function, acronym ReLU, is a curve linear function that produces an output the input directly if it is positive; otherwise, it outputs zero. It's become the default activation Function for many types of neural networks because it is easier to train and often results in better performance [70-71].

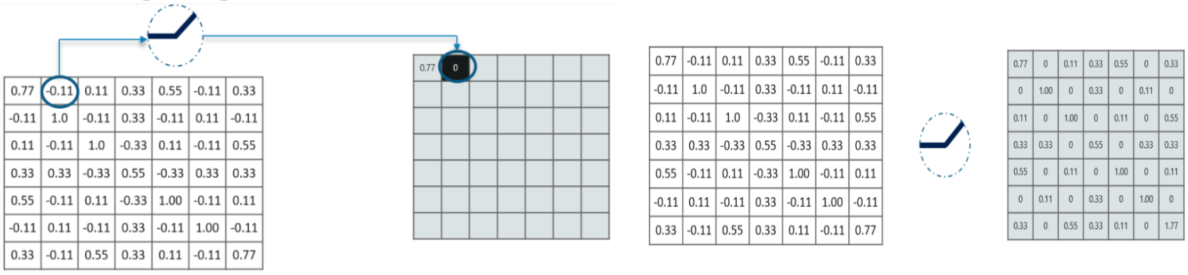

Fig. 6: After ReLU negative values are replaced by 0

Pooling:
This network shrinks the image stack into smaller sizes. Choose a window size of 2 or 3 and move it over the full matrix obtained after moving into the ReLU layer. We only carry a large value from there in order to minimize the image. When an image is pooled, it shrinks in shape. [72-74].

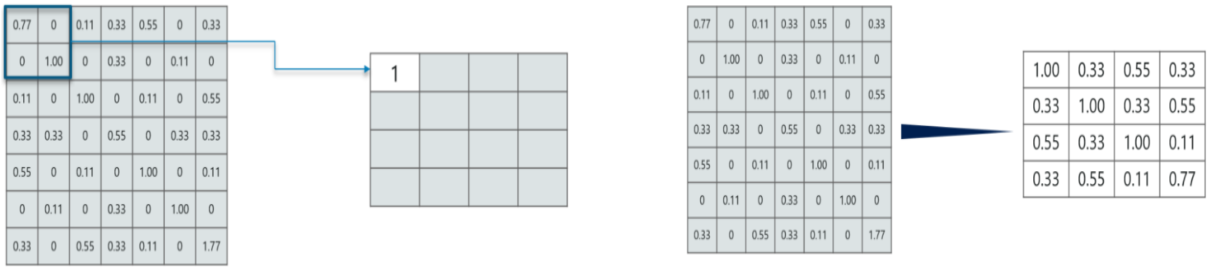

Fig. 7: After maxpooling image matrix 7 x 7 to 4 x 4

The above figure shows the window size 2 so we get 4 values in matrix. If we choose maxpooling then maximum number 1 will be taken from the 1st window.

Stacking the Layers:

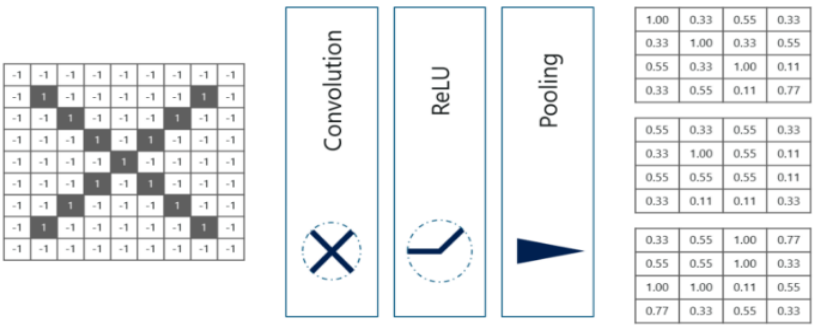

Fig. 8: above image shows image of 7x7 becomes 4x4 after Convolution, ReLU and pooling layer.

Here convolution, ReLU and Pooling is performed in a loop to shrike the image more.

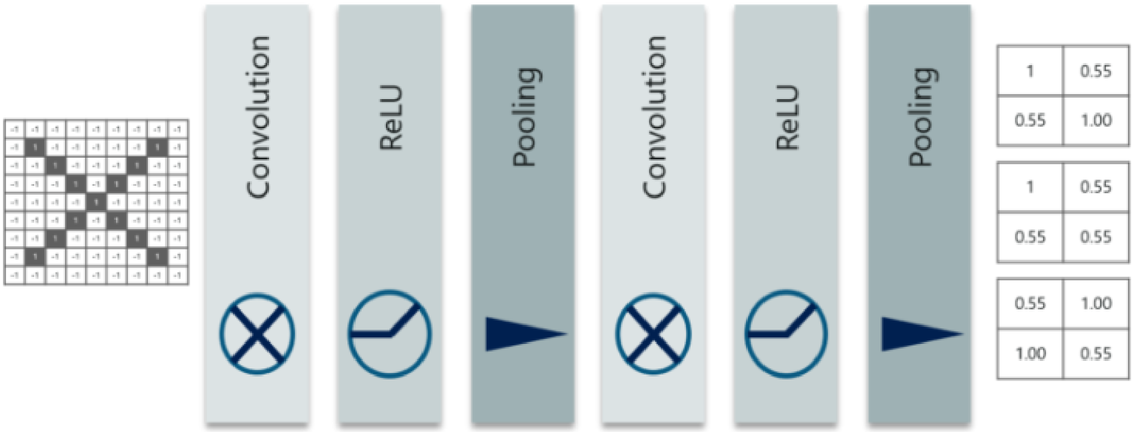

Fig. 9: Image shows looping of Convolution, ReLU and pooling lay**er**

The network's end layers are fully connected, which means that convolution layer neurons are connected to hidden units [75-78]. This is analogous to greater reasoning, which considers most potential outcomes from inputs and outputs. The fully connected layer is the top part in which categorization occurs. Following sources, we combine our filtered and shrunk final image list:

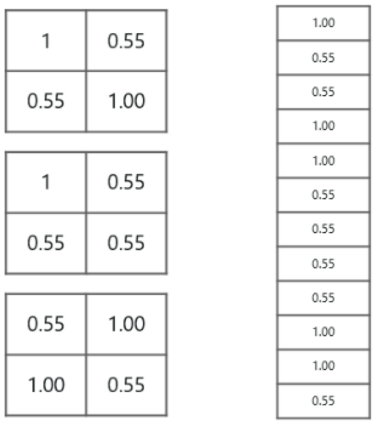

Fig. 10: Filtered and shrunk images in single vector

When we feed brain Tumor dataset images some elements in the vector are high. In the following image 2nd, 3rd, 9th, and 12th elements are high.

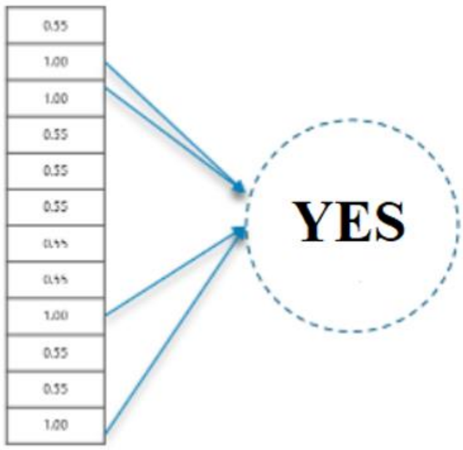

Fig. 11: Filtered and shrunk images in single vector

After training the network it should start predicting and check the working of the classifier. It should start predicting based on the output data.

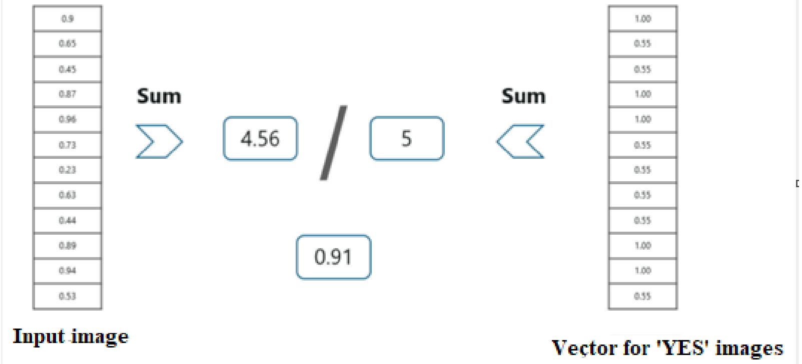

Fig. 12: Filtered and shrunk images in single vector

6. UNDERSTANDING THE NEURAL NETWORK ARCHITECTURE :

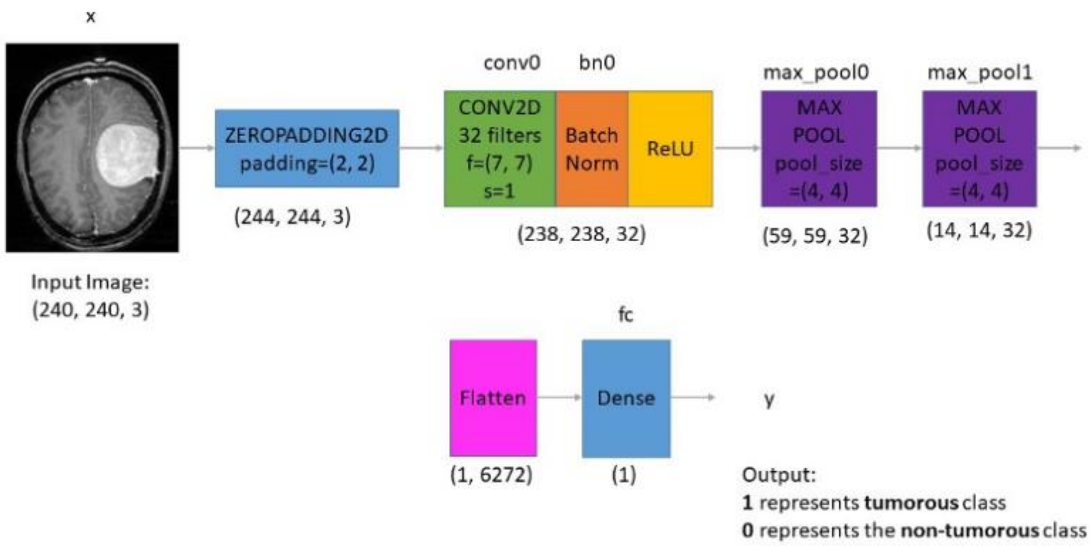

Fig. 13: Neural Network Architecture

Each image x of the shape 240, 240, 3 is loaded into the neural net. The different neural architecture layers that each input image passes through are listed below. [79-81].

i. Zeropadding2d Layer is zero padding for 2D input images. This layer can add rows and columns of zeros to an image tensor's top, bottom, left, and right sides.
ii. CONV2D of 32 filters of (7, 7) matrix and stride of 1.
iii. Batch normalization layer where pixel values are normalized to speed up computation.
iv. ReLU activation is used to introduce nonlinearity in images.
v. Max Pooling layer is used to decrease the computational cost.
vi. The flatten layer is used to convert a 3D matrix to a 1D vector.
vii. Dense is a fully connected output unit.

7. ANALYSIS OF EXISTING SEGMENTATION APPROACHES :

Different classification algorithms are used in computer-aided diagnosis in advanced diagnosis. Implementing the best method is critical for obtaining accurate results in Image Processing and classification [82].

Table 3: Analysis of different segmentation approaches:

S. No.	Classification Method	Paper Published	Datasets used	Results	References
1.	HLS (hybrid level set) classification	2005	10 Brain MRI	Findings of this study could be useful as a diagnostic process as well as a technique of assessing disease activity during treatment.	[83]
2.	A semi-automatic technique depending on specific or population data	2013	138 Brain MRI	Test findings show this approach is resistant to brain Tumor segmentation in terms of both exactness.	[84]
3.	A fully automated generative method	2015	BRATS 2013 dataset	This method outperforms present condition techniques while being unattached either to actual implementation procedure.	[85]
4.	Expectation maximization	2016	SPES dataset	Procedure is extremely adaptable and can identify the certain severity anomaly, making it perfect for identifying many abnormalities such as cancers.	[86]
5.	Otsu algorithm	2017	BRATS 2013	Studies show that the suggested structure outperforms many approaches in identifying neurological disorders.	[87]
6.	Non-negative matrix factorization (NMF)	2017	21 Brain MRI	Most images had accurate findings, though meticulous spatial classification is conditions worsen	[88]

				inadequate classification.	
7.	HCSD (Hierarchical Centroid Shape Descriptor)	2017	BRATS 2012	Results reveals improved significantly achieves the exactness of the state-of-the-art research paradigm. Besides, it outperforms the competition in the pattern classification project.	[89]
8.	Improved thresholding method	2018	Harvard and Private collected images	An automation process that identifies and grades HR disorder that use the Process would take Percentage is described.	[90]
9.	Novel Saliency method	2018	BRATS2013 Challenge	An authentic medical Magnetic resonance data source, the suggested BA supported. Tsallis edge detection and RG categorization outperforms.	[91]
10.	BA and RG	2018	BRATS2015 Challenge	Outcome of the study shows that the implemented procedure improves the Dice, Jaccard, specificity, sensitivity, precision, and accuracy values for BRATS MRI Image.	[92]
11.	EM and FODPSO	2019	192 Brain MRI	Suggested scheme identified blood clot abnormalities with a correctness of 93 percent to use the RF prediction model,	[93]

				which outperformed the findings of the Classification model.	
12.	Adaptive threshold and morphological operations	2019	1340 Brain MRI	The program's achievement has been proportionally tested and evaluated by industry professionals.	[94]
13.	3D semantic segmentation	2020	BRATS 2019 challenge	In enhancing accuracy rate, we investigated industry standards in 3-dimensional classification tasks, such as conventional converter structure and combined activation functions.	[95]
14.	CNN Model	2021	FLAIR (T1T 1C, T2) weighted	Alik svm classification performance measures as well as 3-dimensional image analysis could be perceived as helpful for method outperforms neurological disorders.	[96]

8. RESEARCH GAP :

A review of the literature revealed that brain tumour segmentation is one of the most essential issues of the medical sector. Making an accurate CNN is a tough challenge. As Medical field is a wide area for research. This survey identifies and proposes solutions to the following research gaps.

Research Gap 1 : To set CNN hyper parameters using optimization methods.
Research Gap 2 : To find new approach to classify different types of brain tumor.
Research Gap 3 : To concentrate on Turing more hyper-parameters by increasing the number of Convolutional layers and filters in each Convolutional layer.
Classification algorithm can be fine-tuned further before being tested on real-world images to determine its utility as a tool in diagnosing diseases.

9. PROPOSED ARCHITECTURE FOR BRAIN TUMOR DETECTION :

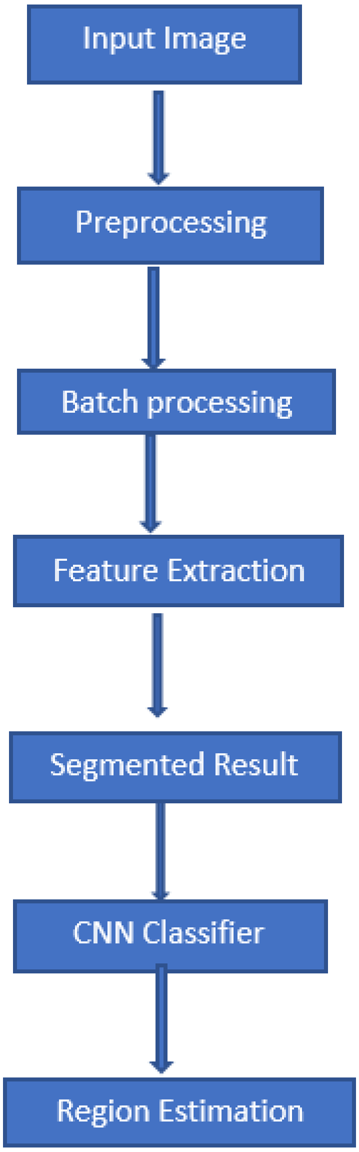

Fig. 15: Predictive Model of Brain Tumor detection

Dataset is collected in the initial step. Collected dataset images are pre-processed. Then images are enhanced and noise is removed. Feature extraction is done using the filter matrix. Depending on the feature extracted segments are made. Now Using CNN Classifier classifying the images according to the region estimation to Tumor and non-Tumor images [97-98].

10. RESEARCH AGENDA :

i. To increase the image quality.
ii. Finding a large dataset for training the model.
iii. To maintain patient data privacy.
iv. Finding the best algorithm to detect brain Tumor detection.
v. Finding any new technologies in neural networks for medical image processing.
vi. Finding out the new challenges in medical image processing.

11. ANALYSIS OF RESEARCH AGENDA :

The data obtained could be evaluated using different approaches. The goal of this study is to create an optimization approach that will produce the most effective classification results. Accuracy of the research is explicitly affected by the quality of the input images gathered, that must be enhanced using noise filtering techniques [99]. Patients' confidentiality will be a huge problem throughout the study. Data gathering for various kinds of brain tumor would be a difficult task. Predicting preliminary stage diagnosis with extreme accuracy is a massive issue that is addressed later. An early prediction of symptoms is a great help because they can reduce their chances of becoming affected by attempting to make aspects of regular life. Advancement of auto symptom recognition will be very beneficial to oncologists because manual tracking is no longer required, and the solution is obtained with good accuracy. It can be useful in finding out the possibility to classify other diseases effectively.

12. FUTURE ENHANCEMENT :

Deep learning is a promising trend that has spawned a new reality and it has progressively proven its effectiveness in a variety of computer vision applications. Medical images are challenging and deciding things concerning them necessitates the use of technical expertise and complex classification technologies employed. Considering their ability to rapidly extract features, convolutional neural networks are used more in this kind of condition. It will start a process of usage and progress, and we wish to discover deep learning techniques, such as the convolutional neural network, used in a number of visual production application fields. We intend to use 3D brain images in the future to obtain more accurate brain cancer categorization. Dealing with a huge dataset are more complex in this regard, and we want to create a data source focusing the obscure on relation to our country, which will allow us to complete our work more quickly.

13. ABCD RESEARCH PROPOSAL ANALYSIS :

ABCD approach is said to evaluate the aspects of the system and the effectiveness of the methods that are to be applied in way of life [100-105]. The process and its attributes are studied, and significant improvements are needed using four aspects: advantages, benefits, constraints, and disadvantages.

Advantages:

i. It provides algorithms which detect early-stage cancer.
ii. Diagnoses of types of Tumors.
iii. More trustable than Manual detection.

Benefits:

i. Oncologists and Radiologist are benefitted.
ii. Save life if detected in early stage.

Constraints:

i. Cancel detecting model can be more accurate if it is trained using large datasets.
ii. Difficult to select the most accurate algorithm.
iii. Model is not user-friendly. Radiologists need to be trained.

Disadvantages:

i. False detection can leads to wrong treatment procedures.
ii. Finding Most Accurate model is a difficult process. Model should be trained with large datasets.

14. FINAL RESEARCH PROPOSAL IN CHOSEN TOPIC :

The final research topic is an innovative MRI study that explains for brain tumor segmentation using Convolutional Neural Network.

15. RESEARCH FINDINGS AND DISCUSSION :

Following are the Challenges found in the area:

- A brain tumor grows quickly in size. As a result, detecting Tumor s at an early stage is a difficult task.
- Due to strong magnetic fluctuations in the coil, brain Tumor segmentation is difficult on MRI images.
- Another complex process is the optimization and selection of the best features in brain tumor classification.

16. THE PROPOSAL'S LIMITATIONS :

The above proposal is only for detecting brain tumours. A similar proposal can be developed for any other cancer type detection, such as breast cancer, lung cancer, bone cancer, and so on. The whole proposal provides information such as if brain MRI images are tumorous or not, but it never predicts if a tumour is cancerous or not.

17. CONCLUSION :

The Convolutional Neural Networks are still a trend in the field of automated Tumor segmentation. This is essential for medical experts to understand deep learning techniques in terms of planning to use these techniques in diagnostic future practices. This paper provides a basic overview which enables the researcher to be well into the community of automated segmentation. This could be applied to other areas of radiation oncology with such advancements of machine learning techniques in brain cancer. Deep neural networks are a powerful technology will most possibly assist neurosurgeons in generating useful care for individuals.

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