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DETECTION OF TUMORS IN HUMAN ENCEPHALON USING CONVOLUTIONAL NEURAL NETWORK

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***Abstract* -** The principal controller of a human being is their brain. A brain tumor develops when cells in the brain grow and split abnormally; brain cancer develops when brain tumors continue to grow. Computer vision plays a significant role in the field of human health, replacing human judgement, which provides reliable results. The common imaging techniques for magnetic resonance imaging (MRI) that are likely to be the most dependable and comfortable include CT scans, X-rays, and MRI scans. MRI finds even the smallest objects. The goal of our paper is to raise knowledge about the many methods for using brain MRI to find brain tumors. In order to remove the noises that can be seen in an MR image, we finished pre-processing utilizing the bilateral filter (BF) in this analysis. Following this for accurate tumor region recognition were binary thresholding and Convolutional Neural Networks (CNN) segmentation algorithms. Datasets for training, testing, and validation are used. We can determine whether a brain tumor is there or not depending on our device. The outcomes that are produced can be evaluated using a variety of performance-tested measures, including accuracy, sensitivity, and specificity. It is reported that the proposed development may demonstrate higher-quality functionality than its competitors.

Keywords— Convolutional Neural Network & It's layers. Related work, Proposed System, Data sets, Results & Conclusion.

I.INTRODUCTION

The brain tumor is truly certainly one of the human body's maximum essential organs, is fabricated from billions of cells. Unconfined cellular department results in the formation of a tumor that is an unusual series of cells. Brain tumors are categorized into: low-grade (grades 1 and a couple of) and high-grade (grades 3 and above) (grade 3 and grade 4).This tumor is one that isn't always cancerous. Further, a malignant is also known as high grade tumor. This tumor isn't always a cancerous neoplasm. As a end result, it can not outspread to specific thoughts regions. A cancerous tumor, on the opposite, is a malignant neoplasm. As a quit result, it hastily extends to other components of the body with no discernible borders. It results in immediately loss of life. Brain MRI Images are used generally for tumor identification and tumor progression modelling. The primary applications of this information are in tumor evaluation and remedy. An MRI test well-known shows extra records unique medical diagnosing than a CT or ultrasound Images. An MRI test can be used to discover any unusual occurrence in thoughts tissue and offers unique statistics on the Brain's shape. students furnished precise computerized strategies for locating Brain cancers and cataloguing classifies the use of thoughts MRI Images from a time while clinical imaging can be digitized and transmitted to a System. In contemporary years, however, procedures together with neural networks (NN) and help vector machines (SVM) have typically been used for their achievement. Nowadays, Deep Learning (DL) have established a concept on machines getting to know, as the underground structure can correctly represent complicated relationships without the need for a big range of nodes, as floor architectures consisting of k-Nearest Neighbor (KNN) and Support Vector Machine (SVM). As a result, they've swiftly expanded and superior in fields unrelated to fitness informatics, together with clinical picture evaluation, clinical informatics, and bioinformatics. As a give up result, in this evaluation, we endorse a convolutional neural Networks-based completely approach for detecting brain tumors (CNN).

II.RELATED WORK

The tumor and non-tumor unfastened quantities of the brain are outstanding the usage of fuzzy C-method (FCM) segmentation. The wavelet functions also are withdrawn using a multilevel discrete wavelet rework (DWT). Ultimately, to exactly classify brain cancers, a Deep Neural Networks (DNN) is carried out. This approach is contrasted with KNN, Linear Discriminant analysis (LDA), and Sequential minimum Optimization grading processes (SMO). Despite the fact that the complexity is extra and the execution may be very poor, brain tumor class analysis using DNN has a 96.97% accuracy fee [1].

A singular bio-physio mechanical tumor boom modelling that dissects affected person tumor progression level by means of level. it will likely be used to locate a large tumor mass effect in gliomas and stable tumors with awesome margins. Combining discrete and non-stop techniques is used to create tumor increase modelling. To provide probability-loose segmentation of tumor-bearing brain pix, the proposed method employs atlas-based totally registration. The number one utility of this method is brain tissue segmentation. Yet the calculation system will be time-eating [2].

New multi-fractal feature extraction (MultiFD) and refined AdaBoost class strategies that are used to hit upon & phase brain tumors. the texture of brain tumor tissue is extracted the usage of the MultiFD characteristic extraction approach. AdaBoost's improved class techniques are used to determine whether or no longer a given piece of brain tissue is malignant. there are numerous complications [3].

Impartial Projections primarily based classification (LIPC) approach classifies brain voxels. The course element is likewise derived the usage of this technique. As a end, LIPC requires no specific regularization. Low precision [4].

The comparison of a graph-based tumor segmentation method to a seeded tumor segmentation approach the usage of the new mobile Automata (CA) generation. The Volume of Interest (VOI) and seed selection are evaluated for powerful brain tumor segmentation. This research also includes tumor slice subdivisions & Low degree complexity. However, the precision is negative [5].

A multimodal brain encephalon segmentation scheme, additionally mentioned as a new brain tumor segmentation scheme, is provided. In phrases of overall performance, combining a extraordinary segmentation algorithm outperforms the modern-day technique. but, there are numerous headaches [6].

Liu J et al d., proposed an multimodal brain tumor segmentation scheme, also called a new brain tumor segmentation, is presented. In terms of overall performance, combining a specific segmentation algorithm outperforms the contemporary method. However, there are various complications [7].

Huda S et al introduced Hybrid feature selections and ensemble type which are used in diagnosing brain tumors. The GANNIGMAC, selection tree, and Bagging C techniques are used to generate the decision regulations. Additionally, to streamline choice-making processes, use hybrid characteristic selection which is a mixture of GANNIGMAC + MRMR C + Bagging C + decision tree [8].

The fuzzy Interference system (FIS) is a one-of-a-kind approach for brain segmentation. The fuzzy controller's membership feature is created the usage of supervised classification. While accuracy is low, overall performance is high [9]. Janani and Meena P. Adaptive histogram equalization is used to boost picture variance. The tumor is then detached from the complete brain Images with the help of a segmentation system based on fuzzy C-manner (FCM). Following that, Gabor traits are derived on the way to take away ordinary brain cells. Fuzzy class with k-Nearest Neighbor (KNN) class is used to stumble on unusuality's in a brain MRI photo. There are various complications. However, the accuracy is less. Convolutional neural networks are used on this look at to gain a modern automatic categorization of brain tumors [10].

The 2010 paper "Brain tumour extraction from MRI images using Matlab" by Bhalchandra et al. addressed the tumor of The flooded watershed segmentation approach and the morphological operation are presented in this work [11].
B. Devkota, Abeer Alsadoon, P.W.C. Prasad, A. K. Singh and A. Elchouemi, "Image Segmentation for Early Stage Brain Tumor Detection using Mathematical Morphological Reconstruction" proposed that their study suggests a computer-aided detection method that uses Mathematical Morphological Reconstruction to detect brain tumors in their early stages (MMR). To locate regions of interest with likely tumors, an image is first segmented and pre-processed to reduce noise and artifacts [12].

The unpredictable appearance of tumor tissue in practical applications, segmenting a brain tumor using magnetic resonance imaging is a difficult and time-consuming task. A novel level-set based model for tumor segmentation from multi-modality magnetic resonance imaging is proposed in this research. With three classes: tumor, edema, and healthy tissue in creating the tumor segmentation at the pixel level [13].

The definition of a tumor location in the brain using MRI scans is described in this research utilizing a computer-based method. It is first determined whether the brain is tumor-free or has a tumor, and then it is determined whether the tumor is benign or malignant. The approach includes phases for picture preprocessing, segmentation, feature extraction, and classification using neural network methods. As a final step of confirmation, the region of interest approach is used to define the tumor area. The proposed approach has been put to the test using a user-friendly Matlab GUI software [14].

A unique technique has been proposed for combining cell density patterns produced by tumor development models to enhance texture-based tumor segmentation. We use the Lattice-Boltzmann approach to solve the reaction-diffusion equation and describe tumor progression (LBM). The cell density distribution that could potentially reflect the anticipated tissue placements in the brain additionally is obtained by computational tumor growth modeling. In order to improve brain tumor segmentation in MRI, the density patterns are then taken into consideration as novel characteristics alongside other texture (such as fractal and multifractal Brownian motion (mBm)), and intensity features [15].

An automated brain tumor classification system which was implemented using probabilistic neural networks along with imaging and data processing techniques. Human analysis is the traditional approach for classifying medical resonance brain images and finding malignancies. Operator-assisted classification techniques are non-reproducible and unworkable for vast volumes of data. Medical resonance pictures have operator performance noise that can cause substantial categorization errors. Fuzzy logic, neural networks, and other artificial intelligence techniques have demonstrated considerable promise in this area. Therefore, the Probabilistic Neural Network was used in this paper to achieve the goals. There were two parts to the decision-making process: feature extraction using principal component analysis and probabilistic neural network (PNN) [16].

An Initial tumor segmentation which was carried out using region-based fuzzy clustering, and the results are used to generate an initial contour for a deformable model. The final contour for the precise tumor border is then determined utilizing a gradient vector field as an external force field [17].

Analysis of brain MR images from various perspectives and usage of several segmentation networks. By contrasting the findings with a single network, the effectiveness of using distinct networks for segmenting MR images is assessed. One network can attain a Dice score of 0.73, while several networks can achieve a Dice score of 0.79, according to experimental network evaluations [18].

A brand-new hybrid method based on fuzzy c-means and the support vector machine (SVM) is put forth. The intended algorithm is a hybrid method for brain tumor prediction that combines fuzzy c-means and support vector machines (SVM). This algorithm uses enhancement methods including contrast improvement and mid-range stretch to improve the image. Skull striping uses morphological techniques and double thresholding. To find the suspicious region in a brain MRI picture, fuzzy c-means (FCM) clustering is utilized to segment the image. After extracting features from the brain picture using the Grey Level Run Length Matrix (GLRLM), the brain MRI images are classified using the SVM technique, which yields more precise and efficient results [19].

III.PROPOSED WORK

The human encephalon is simulated using neural network architecture and execution. There are types of neural networks predicated on how they connect. The three types are recurrent, feedforward, and feedback neural networks. Feed-forward neural networks can also be classified as single-layer or multi-layer networks. In a single-layer network, the hidden layer is invisible. However, it only has input and output layers. Whereas, A multi-layer comprises of an input layer, a hidden layer, and an output layer. Recurrent networks are closed-loop feedback systems.

In Figure.1, The block diagram depicts a convolutional neural network-primarily based brain tumor classification technique. CNN divides the classification of mind tumors into two levels: training and testing. Tumor and non-tumor brain images, for example, are of the various classes into which the photos had been labelled. all through the training segment, pre-processing, precise feature, and classification using the Loss function are finished to expand a prediction model.

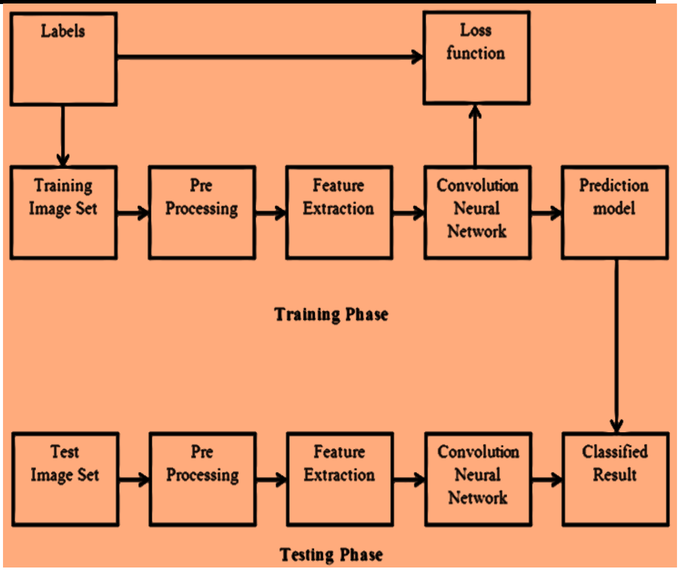

Figure. 1, Block diagram CNN architecture of Brain Tumor detection

First, labeling is performed for a sequence of practice images. Resizing is a technique used in image training. In the end, brain tumors are categorized automatically the utilization of a convolutional neural network. The dataset of brain images is furnished by means of the imaging networks. The image net is one of the early-educated models. To educate from the beginning layer, you ought to educate the entire layer, i.e. the ultimate layer. As a result, there's a exquisite time commitment. It has an impact on output. To keep away from issues like this, the classification phases are carried out using a early-trained modeled mind dataset. We will only train the finishing layer of the Python implementation of the counseled CNN. However, not every layer has to be taught. As a result, the proposed brain tumor computerized category method outperforms the opposition while requiring minimum calculation time.

Loss functions are computed with the help of gradient descent. The pixels of an image is transformed into a class score the usage of the rating characteristic. A loss characteristic evaluates the quality of a hard and fast of parameters. it's points decided by way of how well the triggered ratings matched with the best labels inside the training information. to enhance accuracy, the loss function need to be carefully calculated when precision is less but loss characteristic is high. further, with a small loss characteristic, accuracy will increase. The gradient value for the loss function is received to determine the gradient descent algorithm. Iteratively compare the gradient value to calculate the gradient of the loss function. First layer application of a convolution filter. Smoothing is achieved for the convolution filter out, additionally referred to as subsampling, lowers the sensitiveness of the filter. The activation layer controls how a signal passes from a layer to the following. increase training efficiency through the usage of corrected linear units (RELU). every neuron in the layer underneath is coupled to the neurons within the layer above, a loss layer is included for issuing feedback to the neural network at the end of training.

A. *Convoultion Neural Network (CNN)*

Convolutional Neural Networks (ConvNet/CNNs) are deep mastering algorithms takes an enter image, assigning significance (learnable weight and bias) to various factors/gadgets within the picture, and differentiating one from the opposite. ConvNet calls for drastically much less preprocessing than other category strategies. ConvNets can adapt those filters/traits with required education, at the same time as primitive procedures require the introduction of the filters manually.

The ConvNet network's structure changed into inclined via the visible Cortex enterprise that is much like the connecting architecture of neurons inside the human mind. Special neurons reply to inputs simplest in a small vicinity of the field of vision called the Receptive subject. a chain in such fields that overlap covers complete visual field. A regular neural Networks does not assist picture scaling.

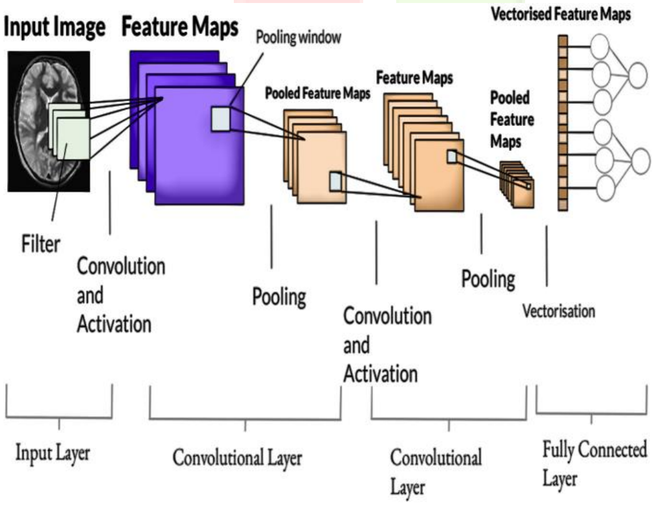

Figure. 2. CNN architecture for brain tumor analysis

Given in Figure. 2., Convolutional neural networks, however, support image scaling, which converts the quantity of the enter photo to that of the output image (duration, width, peak). A convolutional neural Networks including an enter layer, a convolution layer, a rectified linear unit (ReLU) layer, a pooling layer, and a totally related layer (CNN). In a convolutional layer, an input image is classified into numerous tiny parts. The function activation function is done in the ReLU layer. The pooling layer is primarily carried out for sampling. The fully linked layer is utilized in the last layer (i.e.) to offer a category rating or label scores based on a possibility among 0 and 1.

In Figure.3, The method for detecting brain tumors is depicted in block diagram form above. MRI scans are first collected for analysis.

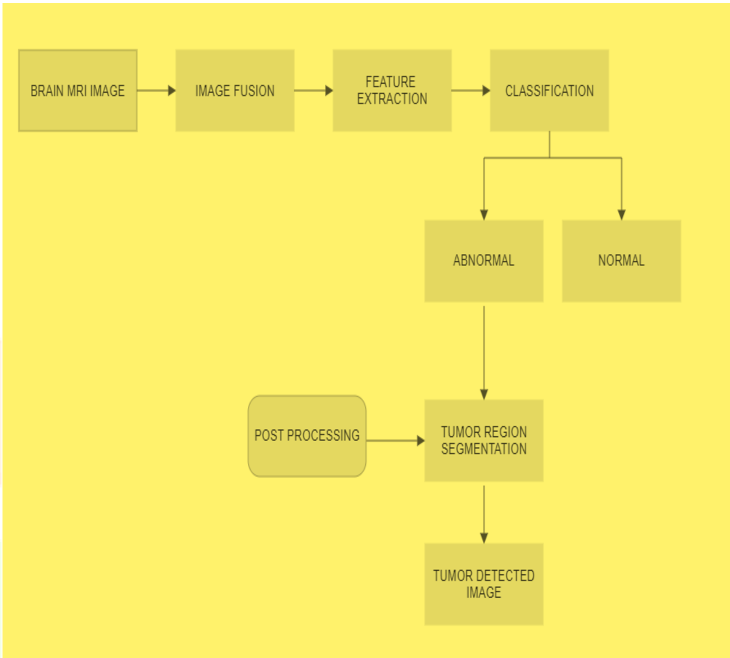

Figure. 3. Structure of CNN for detecting Brain Tumors

It is then modified to extract only the brain-related portion of the image from the acquired data. The CNN architecture required a size change for MRI, which was accomplished (224,224). It is possible to extract distinct MRI variations and thus expand the training datasets by moving, resizing, rotating, and panning the data. As input, the CNN model can process enhanced images. In the context of an appropriate learning environment, a CNN model is created to detect brain tumors. Following training, testing and model validation examine the model's effectiveness and correctness. The model provides a probabilistic output that aids in analysis of existence of a brain tumor in the MRI.

B. *CNN Layers*

Convolution Layer

Convolution is the combination of two functions with strong arguments. In the convolutional layer, parallel convolution is used to generate a set of linear activation functions. A subsequent non-linear activation layer is used to apply non-linear changes such as the Rectified Linear Activation Function (ReLU).

Rectified Linear Activation Unit (ReLU) Layer

Hyperbolic tangent activation, softmax activation, and changed linear block activation are the maximum commonplace approaches to output a convolutional layer for nonlinear mapping. We choose ReLU because the activation characteristic for CNN. ReLU is expressed mathematically as follows: while a neuron receives x as inputs, f(x) = max (0, x) ReLU is more efficient than logistic sigmoid features and extra sensible than hyperbolic tangents for convolutional networks. As a end result, ReLU is now the most normally used activation feature in CNNs.

Pooling Layer

The usage of each characteristic of the convolutional layer may be very taxing at the category manner. by default, the merge feature replaces network output with a summary of the output closest to a detailed area. The activation of the merged map can be much less sensitive to the correct positioning of the image shape than the activation of the authentic functional map because of the merge manner. due to the fact one of a kind pull features behave in a different way, this essay employs a spread of pull techniques. In our project, we used the Maxpooling2D technique.

C. *Code Of CNN Model*

```
model = Sequential()
model.add(Conv2D(32, kernel_size=(2, 2),
input_shape=(128, 128, 3), padding = 'Same'))
model.add(Conv2D(32, kernel_size=(2, 2), activation ='
relu', padding = 'Same'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Conv2D(64, kernel_size = (2,2),
activation='relu', padding = 'Same'))
model.add(Conv2D(64, kernel_size = (2,2), activation
='relu', padding = 'Same'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(2, activation='softmax'))
model.compile(loss = "binary_crossentropy", optimizer='
Adam',metrics=['Accuracy'])
print(model.summary())
```

Figure. 4. sample code for cnn model

In Figure.4., Deep learning models can be created using the Sequential Model API by generating instances of sequential classes and adding model layers. A 2D convolution layer is called Keras Conv2D. With the layer input, this layer aids in the creation of a hoisted convolution kernel, which yields a tensor as the output. Batch normalization applies a change that moves the output's standard deviation and mean closer to 1 and 0 respectively. During the training period, the dropout level randomly sets the input units to 0 at a rate of 0 at each step. By doing this, overfitting is avoided. The sum of all inputs is kept constant by scaling up inputs that are not set to 0 by 1/(1 - Rate), and the input is then flattened. Each neuron in the dense layer of a neural network receives information from every neuron in the layer below it due to the layer's extensive connections.

D. *ALGORITHM*

	Convolution filters first layer application.
	Smoothing the convolution filter, or subsampling, lowers the filter's sensitivity.
	The activation layer adjusts on how a signal moves from a layer to another.
	Improve training efficiency by utilizing corrected linear units (RELU).
	Every neuron in the layer below is coupled to the neurons in the layer above.
	Loss layer is introduced at the finishing stage of training to issue feedback to the neural network.

E. *Datasets*

We have collected two datasets has 2 folders: yes and no which contains 253 Brain MRI Images. The folder yes contains 155 Brain MRI Images that are tumorous and the folder no has 98 Brain MRI Images that are non-tumorous.

Configurations to implement the brain tumor detection are:

<u>Hardware Requirements</u>

- Processor: Intel core i5 or above.
- 64-bit, quad-core, 2.5 GHz minimum per core
- Ram: 4 GB or more.
- Hard disk: 10 GB of available space or more.
- Display: Dual XGA (1024 x 768) or higher resolution monitors.
- Operating system: Windows 8.1 or above.

<u>Software Requirements</u>

- Programming Language: Python.
- Environment: Jupyter.
- Libraries: Os, Keras - 2.11.0 and tensorflow – r2.11

Figure. 5. Tumor and Non Tumor image datasets

We have collected datasets from LUCID and IGNITE diagnostic centers at KARKANA,HYDERABAD. The datasets contains different type of tumors such as Glioma, Meningioma and Pituitary. Our data set contains Two in plane resolutions as follows are:

- High Resolution (HR) 0.50 * 0.50mm^ 2
- Low Resolution (LR) 0.80 * 0.80 mm^2

HR Information Detailed data on 64 subjects. Images of SWI phase and scale were used to represent each of the 193 people in the LR data. This dataset-labeled folder contains Excel files with the same names as the data in the Data folder. The Image datasets has contains as tumor and non - tumor image datasets which are provided.

IV.EXPERIMENTAL SETUP & RESULTS

Procedures done for brain tumor detection are:

<u>Data Preprocessing</u>

The following preprocessing procedures were used on each image:

i) Cropping the area of the picture that solely shows the brain (which is the most important part of the image).

ii) Because the images in the collection come in various sizes, resize the image to fit the following shape: (240, 240, 3)=(image width, image height, number of channels). As a result, for the neural network to accept them as input, all images must be of the same shape.

iii) Apply normalization to scale the values of pixels to the range of 0 to 1.

<u>Splitting of data</u>

The data was split in the following way:

i) 70% of the data for training.
ii) 15% of the data for validation.
iii) 15% of the data for testing.

Neural Network Architecture

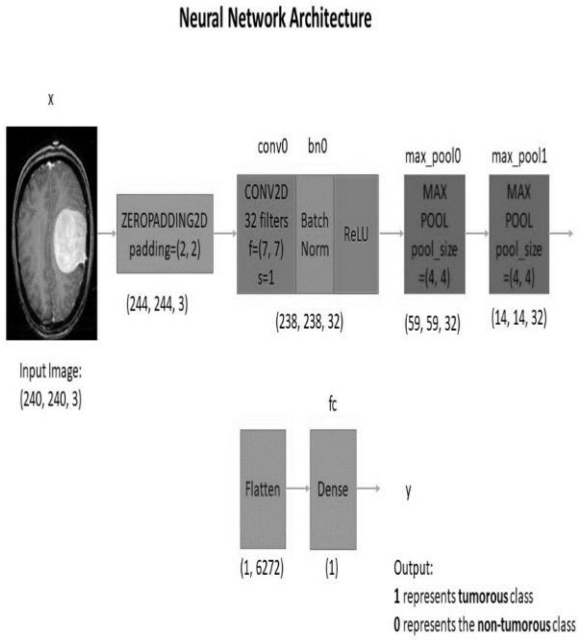

Figure.6. Neural Network Architecture for brain tumor detection

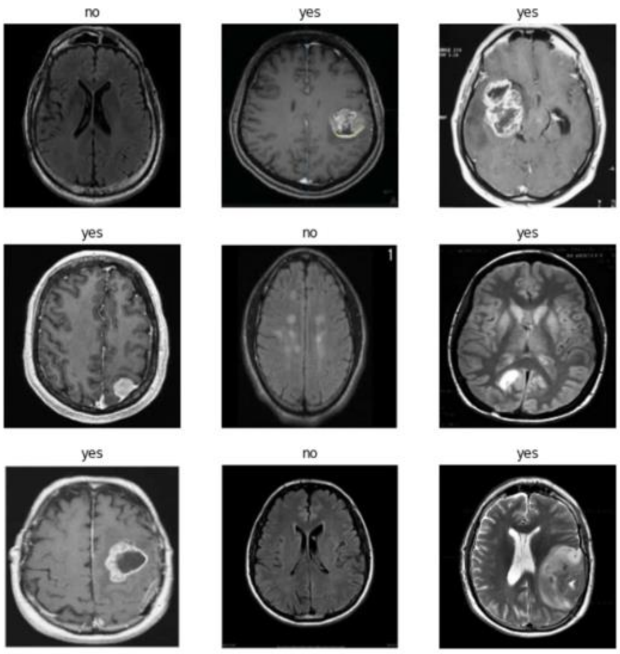

Figure.6. Classifying the Brain Tumor Datasets

Each input x (image) has a shape of (240, 240, 3) and is fed into the neural network. And, it goes through the following layers:

i) A Zero Padding layer with a pool size of (2, 2).
ii) A convolutional layer with 32 filters, with a filter size of (7, 7) and a stride equal to 1.
iii) A batch normalization layer to normalize pixel values to speed up computation.
iv) A ReLU activation layer.
v) A Max Pooling layer with f=4 and s=4.
vi) A Max Pooling layer with f=4 and s=4, same as before.
vii) A flatten layer to flatten the 3-dimensional matrix into a one-dimensional vector.
viii) A Dense (output unit) fully connected layer with one neuron with a sigmoid activation (since this is a binary classification task).

The methods which are based on feature extraction, feature selection, dimensionality reduction, and classification techniques were done for a large volume of medical MRI image datasets .

IV.RESULTS

In Figure.6, The outputs of image datasets are classified into tumor and non-tumor by labeling, preprocessing, feature extraction and convolutional neural network process.

loss		*0.7462427020072937*
tp		*30.0*
fp		*2.0*
tn		*16.0*
fn		*2.0*
score		*11.645279884338379*
accuracy		*0.9545454382896423*
precision		*0.9375*
recall		*0.9375*
auc		*0.9270833730697632*

Table 1: *Tabular description of Validation Results*

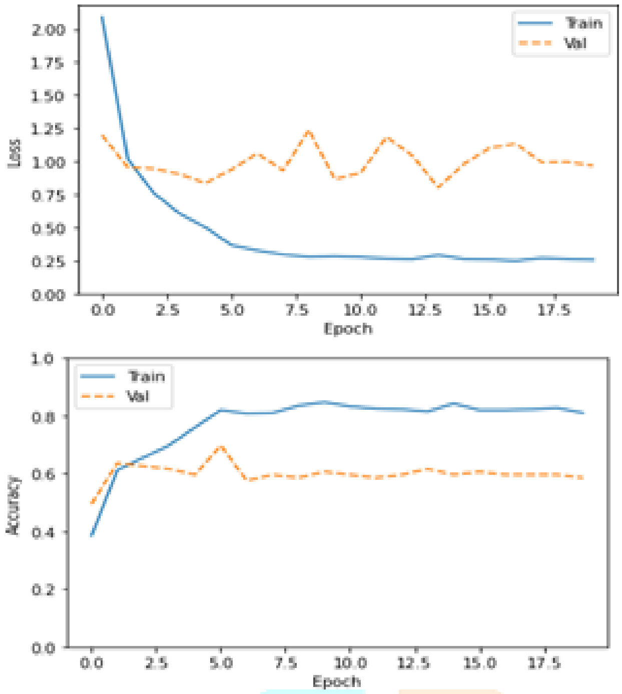

Figure.7. Accuracy graph and Loss graph for output

In Figure.7, For the accuracy graph, 30 epochs were used. In the first two epochs, accuracy rises quickly, demonstrating how quickly the network learns. After that, the curve flattens, indicating that little training epochs are needed to fully develop the model. Overfitting is typically present when the training data accuracy ("acc") keeps rising while the validation data accuracy ("val acc") declines. It shows that the model has begun to learn the data. Since there are 30 epochs in the loss graph, the loss on the training set falls down quickly during the first two epochs. The loss for the test set does not decline as quickly as it does for the training set, but rather stays nearly constant over time. Because of this, our model is generalising.

V. COMPARATIVE ANALYSIS

S. No	Title (Existing Systems)	Techniques	Accuracy	Proposed System Accuracy
1.	Segmentation and Classification of MRI Brain Tumor	Discrete Wavelet Transform (DWT) Gray Level Co-occurrence Matrix (GLCM) Support Vector Machine (SVM)	70%-75%	95%
2	Brain Tumor Segmentation Based on Deep Learning	Cascade Convolutional Neural Network(C-ConvNet/ C-CNN)In Deep Learning	87%-90%	95%
3.	MRI Brain Tumor Classification using Hybrid Classifier	Support vector machine (SVM). KNN classifiers are used to classify tumors in malignant and benign type	85%-90%	95%
4.	Brain Tumor Detection Using Artificial Convolut	Artificial Convolutional Neural Networks	88.25 %-92.5%	95%

	ional Neural Networks			
5.	Brain Tumor Segmentation Using Convolutional Neural Network with Tensor Flow	Convolutional Neural Network (CNN) with Tensor Flow	75%-85%	95%
6.	MRI Brain Tumor Segmentation and Patient Survival Prediction Using Random Forests and Fully Convolution-al Networks	Fully Convolutional Network, Random Forest,Deep learning	88%-90%	95%
7.	Supervised learning based multimodal MRI brain tumor segmentation using texture features from super voxels	Machine Learning texture features from super voxels	89%-94%	95%
8.	multi modal brain tumor Images segmentation benchmark (brats).	SVM, Artificial Neural Network	74-85%	95%
9.	Brain Tumor segmentation and classification using FCM and support vector machine	combination of support vector machine (SVM) and fuzzy c means.	91.77 % (Linear) 90.01 % (RBF)	95%
10.	Improved brain tumor segmentation by utilizing tumor growth model in longitudinal brain MRI	lattice-boltzmann method (LBM)	76.21 %	95%
11.	Tumor-Cut: Segmentation of Brain Tumors on Contrast Enhanced MR Images for Radiosurgery Applications	cellular automata (CA) based seeded tumor segmentation method	85.30 %	95%
12.	Probabilistic Neural Network for Brain Tumor Classification	gray-level co-occurrence matrix (GLCM), Discrete Wavelet Transformations	94.5%	95%

		(DWT)		
13.	Hybrid characteristic choice with Ensemble classification for Imbalanced Healthcare records	Electronic health records (EHRs), Artificial Neural Network	78.8%	95%
14.	Detecting Brain Tumors in MRI Images	Threshold Segmentation	91%	95%
15.	Fuzzy Clustering and Deformable Model for Tumor Segmentation on MRI Brain Image: A Combined Approach	Enhanced Possibilistic Fuzzy C-Means (EPFCM)	82.10 %	95%
16.	Brain Tumor Segmentation Using Deep Learning by Type Specific Sorting of Images	Segmentation	79%	95%

Table 2: *Tabular description of comparative analysis of accuracy scores of different existing systems with our proposed system.*

In Table 2, Our proposed methodology has brought more accuracy comparing to existing systems.

V. CONCLUSION

The main aim of this research work is to model a system for self-categorizing brain tumors that is highly accurate, fast, and simple. Future data will be collected to test the CNN's performance and a perfect CNN with the optimal layer settings and number of layers will be built.

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