Detection of Brain Tumor using Convolution Neural Network

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Abstract— A brain tumor is the most unsafe sickness in humans. It's an strange growth formed in the mind. those tumors are in particular classified into two types one is benign that's non-cancerous and the other is malignant which may be very dangerous for human lifestyles. Early identification of mind tumors can enhance the possibilities of curing. on this exertion, we proposed a Convolution Neural network-primarily based Deep learning version to hit upon the tumor in MRI images. We got very correct accuracy on CNN primarily based version for detecting the tumor in MRI pics. We took 253 patients brain MRI photos and completed records pre-processing and consequently generated a statistics set of 2065 pics. Out of 2065,1085 MRI'S is tumors and 980 of them are non- nontumorous. On this paper, we as compared the result of CNN with other current fashions and VGG16 model.**.**

Keywords— *CNN, VGG16, Deep learning, Convolution..*

I. INTRODUCTION

As in keeping with the facts in the year 2020 there are extra than 10 million deaths alongside with 19 million new cancer instances have occurred and the demise fee is also high in the same 12 months. Mind tumours have occupied a important function in inflicting cancers and it's miles located to be the purpose of demise in most of the cancer instances. Imaging Imaging tests are key tactics in diagnosing mind tumours. To detect the brain tumours. Typically radiologists depend upon radiologists depend upon MRI strategies because it doesn't use ionizing radiation and it is a non-invasive technique. Parveent et.al [1] proposed a model for detection of brain tumor. On this have a look at, Fuzzy C-approach is used for segmentation and SVM for detection, which indicates accurate end result. Later GLRLM is used for extraction of pertinent attribute of a photograph. The categorization method used inside the method is SVM with the aid of using which an accuracy of 83.33% is achieved. Avizenna et.al [2] used inversion recuperation via attenuated fluids in mind approach. BRATS database statistics 2017 is used in this observe, wherein it categorised Magnetic Resonance Imaging (MRI) fix into two classes specifically ordinary brain and bizarre brain. The human frame develops new cells to put returned the vintage or injured cells in a superintend manner, however alternatively, uncontrollable mobile multiplication is located in mind tumor. In step with the documentation of country wide brain Tumor society, the incidence of mind tumors is growing swiftly and observed to be better in more developed countries than in much less developed nations. Imaging assessments like MRI is beneficial in noticing tumors. The file must be diagnosed through doctor and remedy will be started out, but this path of action is tedious. In effect to outplay this, the proposed exertion affords an automatic machine which classifies the tumor and assists the physician in early prognosis. Such that he can carry out the treatment on the earliest. k. P. Danukusumo et.al [3] used Deep Convolution Neural community in their work DCNN which is extraordinary from conventional methods used to extract the functions. In conventional technique to extract capabilities from picture we require an expert of that region, but in DCNN we can extract the capabilities from pix by means of the use of several number of layers which plays a non-linear alteration to compute output categorization.

The important work within the deep getting to know is extracting functions from the photographs. As deep getting to know robotically detects the functions from snap shots that are required for the classification and accordingly the want of a professional for extracting features is omitted. In the paintings proposed by means of LeCun, Y et.al [4]. The Deep gaining knowledge of structure includes minimal three concealed layers, however typically many layers are required which makes it pricey and results in nonlinear function transformation. Every hidden layer consists of a group of neurons which performs a key function in schooling the particular organization of functions relying upon preceeding layer output. The complexity and abstraction of the version increases due to extra quantity of hid neurons as shown in Fig 1.

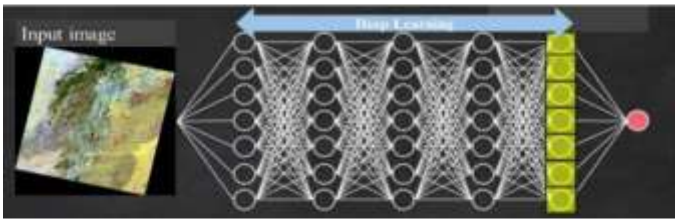


Fig 1. DCNN architecture

S. EDY et.al [5] used DCNN for extracting sophisticated capabilities from the characteristic map. Features that are sophisticated are generated without difficulty with the help of DCNN. The convolution kernel around the input samples to come across several characteristic maps. The detected functions from input samples are represented by means of a small container in function map and then the packing containers are transferred to the maximum series layer that shops relevant features and attenuate the relaxation. Fully Connected layer includes 1D feature vectors from maxpooling layer which may be used to calculate output chance. Configuration of DCNN is shown in Fig 2.

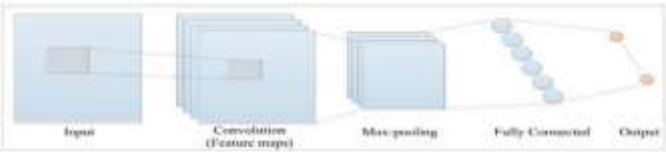


Fig 2. Configuration of DCNN Architecture

The work associated with CNN changed into proposed by S. Hussain et.al [6] of their work, convolution Layer plays a crucial position within the DCNN method. It directly ambitions to extract functions from the given photographs. Convolution plays linear transformation at the input photo wherein the spatial within the records turned into preserved and used for similarly processing. Convolution Layer is the key layer in CNN machine it sights to tug out functions from the input and performs transformation linearly on the input for maintaining spatial records in it. Every weight in the CNN is collected from the enter statistics which is useful for schooling. On this proposed work a CNN is constructed with overall learnable parameters of 249,985 and convolution layers had been used. Consequently as compared to previous techniques cited, our suggestion indicates precise results in accuracy. Even though the efficiency is a piece low whilst as compared with VGG16, the computation time is minimal in our technique as learnable parameters taken and intensity of proposed CNN also are much less.

II. MODEL ARCHITECTURE

In this work, we used a dataset that consists of 253 MRI brain images categorized as "yes" or "no". The label "yes" suggests an image is with a tumor, and "no" indicates the image doesn't consist of tumor. These snapshots are collected from Kaggle datasets. Within the general of 253 images, ninety eight are non-tumorous and the last one hundred fifty five are tumorous. Within the proposed work our essential intention is to dig up the snap shots which include tumor. The flow chart is shown in fig.3.

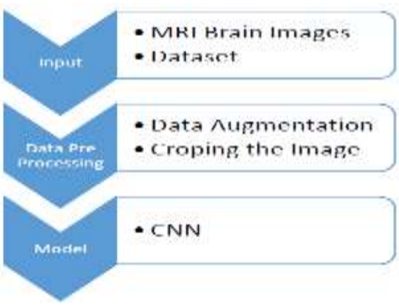
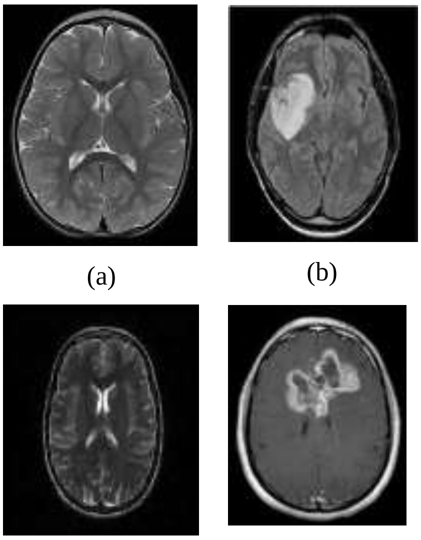


Fig 3. Flow chart of Brain Tumor Detection Model

1. Input: Tumor pictures are accrued from Kaggle such as general 253 MRI shown in fig.4.
Brain MR images with Tumor 155.
Brain MR images without Tumor 98.



(a) (b) (c) (d)

FIG 4 : a), c) without tumor sample.
b), d) with tumor sample.

2. PRE-PROCESSING THE DATA:

Converting the available raw facts into useful format for the building ML version. Then the interpretation is very easy. The step involved in records preprocessing are

1. Required Libraries uploading
2. Appling data Augmentation on facts.
3. Uploading the facts generated from augmentation.
4. Transform all imported snap shots into gray scale.
5. Making use of Smoothing, Erosion and dilation techniques
6. Discover the most important contour
7. Resize the pix
8. Picture cropping
9. Dataset splitting

C. ALGORITHMS:

CNN (Convolution Neural network)

D. OUTPUT:

Education the system for detecting the tumor in input MRI of affected person's to recognize whether or not affected person tormented by tumor or now not.

II. Method

1. Pre-Processing the statistics:

Pre-Processing the information is a method used to convert raw facts into useful information the techniques we are the usage of for facts preprocessing are

a. uploading libraries:

Libraries like Numpy, Tensor go with the flow, Pandas, Matplotlib, Os, etc., are imported to build Neural network.

b. facts augmentation:

To increase the wide variety of photos inside the dataset, image change technique like Rotation Cropping, Flipping, Translation, and many others are used. Image generator elegance is used to generate augmented photographs. The advantage of appearing augmentation is to acquire special snap shots that are helpful for improving the performance of CNN [7]. Prior to augmentation, one hundred fifty five tumorous and 98 non-tumorous images had been found in input facts set and later after applying augmentation the remember progressed to

Variety of examples: 2065
Percentage of advantageous examples: 52.54%,
Range of high-quality examples: 1085
Percentage of bad examples forty seven.45%,
Range of bad examples: 980

c. Import the augmented facts:

The information generated through data generators are imported and bwas chopped for training, validation and testing. The version is educated the use of training dataset shown in fig 5.

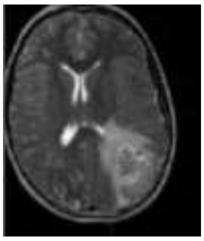


Fig 5. Input photograph

d. Convert the original photograph to gray scale:

gray stage picture is less length when compared to the RGB photo due to the fact all of the sun shades are represented through exclusive grey stages, so we require much less statistics for representing the pixels [8] shown in fig 6.

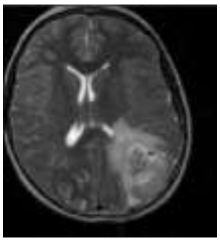


Fig 6. Input image after transformed to gray scale

e. Smoothing and noise removal:

Erosion and dilation strategies are used to dispose of the noise from the pix. In erosion we put off the pixel on the boundary of the image. In dilation we upload pixels at the rims of the photos [9]. For smoothing the snap shots, we are applying a low bypass filter out referred to as gaussian blur filter to dispose of excessive frequency additives in the photograph. Therefore, grabbing the most important contour from the image was executed through locating the boundary of the image shown in fig 7.

Fig 7. Gaussian blur filter applied Image

f. largest contour identification:

Contour is known as the boundary or the picture shape define via the use of Gaussian blur clear out on the input photo [10], we will get the largest contour from the image shown in fig 8 and fig 9.

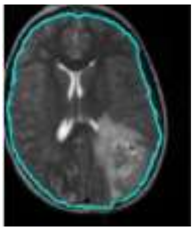


Fig 8. Image with biggest contour

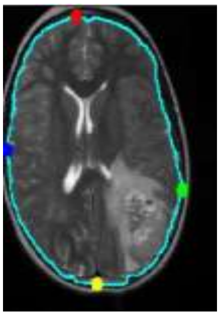


Fig 9. Excessive points within the picture

g. Resize the picture:

In Pre-processing the to be had statistics set having snap shots of various shape and length, we used information augmentation method to improve the range photographs in the dataset after augmentation procedure our actual length of the photographs had been resized to 240X240. For making use of the enter pics to our model it should be higher to have the snap shots with equal length [11].

h. Detach the pix with the help of extreme points:

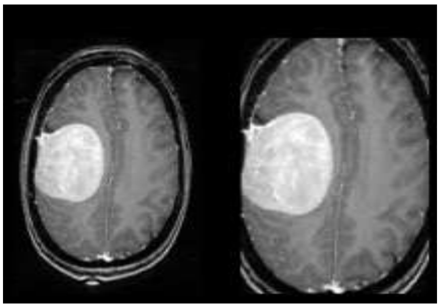


Fig 10. Unique and Cropped picture

i. Splitting of dataset:

The use of teach test split characteristic within the "Keras" we cut up the full records set into train validation and take a look at units. Dataset changed into divided into 3 units of information. Schooling facts the schooling information set consist of general 1445 images and the pictures with tumor are 785 and pics without tumor are 687.

Testing records: The checking out records we generated from the total facts consist of 310 photos a hundred seventy five photographs are tumorous pictures and 135 are non-tumorous photos.

Validation records: The validation facts consist of total 310 images 152 photographs belong to the tumor class and 158 to the non-tumor class.

Convolution Neural community:

In every layer of the CNN include special filters with unique units of coefficients. Extra range of them are used for getting result input and combine them by forwarding to subsequent layer. In this entire exercising CNN hold close the capabilities found in picture [12].

Benefits of CNN:

Neighborhood Invariance: CNN having a very beneficial characteristic its far neighborhood invariance which enables us to categorize a picture no matter role of the item inside the picture become regarded. We are able to have this neighborhood invariance because of the use of "Pooling layer" which can perceive place of our interest.

Compositionality: every clear out generates local direction for lower-degree features to have better-level characteristic illustration. This improves the learning functions of the version from deeper network.

Kernel: its miles a window we are able to expect with the aid of an instance proven below small matrix that

Wrap around the image and provide response at every point with the help of neighbourhood of the image. Example: Convolution mathematically represented as follows

$$O_{ij} = \frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix} * \begin{bmatrix}93 & 139 & 101\\ 26 & 252 & 196\\ 135 & 230 & 18\end{bmatrix}$$

$$= \begin{bmatrix}10.3 & 15.4 & 11.2\\ 2.6 & 28.0 & 21.7\\ 15.0 & 25.5 & 2.0\end{bmatrix}$$

$$= 132$$

The pixel value located at the coordinates (i,j) are set to the value which was calculated by the convolution. By applying convolution filters, and non-linear activation functions. CNNs are able to understand edges and use those features for building the next level layers.

Model Architecture:

The model architecture for tumor detection shown in fig 11.

Layer (type)	Output Shape	Param #
input_3 (InputLayer)	[(None, 240, 240, 3)]	0
zero_padding2d_2 (ZeroPaddin	(None, 244, 244, 3)	0
conv0 (Conv2D)	(None, 242, 242, 32)	896
bn0 (BatchNormalization)	(None, 242, 242, 32)	128
activation_2 (Activation)	(None, 242, 242, 32)	0
conv1 (Conv2D)	(None, 240, 240, 64)	18496
bn1 (BatchNormalization)	(None, 240, 240, 64)	256
activation_3 (Activation)	(None, 240, 240, 64)	0
max_pool0 (MaxPooling2D)	(None, 120, 120, 64)	0
max_pool1 (MaxPooling2D)	(None, 60, 60, 64)	0
flatten_2 (Flatten)	(None, 230400)	0
fc (Dense)	(None, 1)	230401

Total params: 250,177
Trainable params: 249,985
Non-trainable params: 192

Fig. 11.Tumor Detector Model architecture

1. Input layer:

The input layer consists of images which are resized to 240 by 240 pixels with height equal to 240 number of pixels and width equal to 240 pixels with 3 channels of depth as 3.

2. Zero Padding:

We need the edge details in the image so that it's very important to pad Zeros to the borders of an image for getting original size image after applying convolution on it.

Similarly, it's true for filters using inside the convolution.

Example: Image represent matrix form

95	242	186	152	39
39	19	220	153	180
5	247	212	59	46
46	77	133	110	79
156	35	79	93	116

Padding the zeros with pooling size of (2,2).

The zero padding is shown in fig. 13.

0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	95	242	186	152	39	0	0
0	0	39	19	220	153	180	0	0
0	0	5	247	212	59	46	0	0
0	0	46	77	133	110	79	0	0
0	0	156	35	79	93	116	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0

Fig 13. Image after applying Zero padding.

Convolution: Convolution layer is very important for "Convolution Neural Network". In convolution layer we have parameters contain a group of master able K windows [13]. Contemplate the one forward path of the CNN. The process of K-Kernel process shown in fig 14.

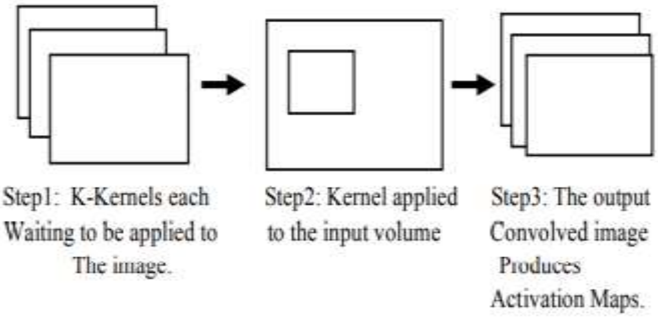


Fig. 14. K-Kernel for convolution

In the present model 32 windows with the size of (7,7) are utilized then the neurons in the model connect to local regions with the size of 7X7 the total weights of the images used by the model is equal to 7X7X3 which is 147. 32 2D activation maps are available in the wake of applying 32 kernels to image that was having input features. Each arrival in output contains only focus on compact area in the input image. Similar to this Model learns windows that are activated for a certain kind of input features. Final image size at the end of convolution has size (238,238,32).

In batch normalization [14] we have a mini batch size for "x" for activation the size of a image moving to next layer is same with respect this batch normalization. The equation given as.

$$\hat{x}_i = \frac{x_i - \mu_\beta}{\sqrt{\sigma_\beta^2 + \varepsilon}}$$

$$\mu_\beta = \frac{1}{M}\sum_{i=1}^{m} x_i$$

$$\sigma_\beta^2 = \frac{1}{M}\sum_{i=1}^{m}(x_i - \mu_\beta)^2$$

This equation implies the activation consists of batch normalization with the value of zero mean and unit variance this helps for network to stabilize the training.it regulate the training process.

Activation:

A Non-linear activation function applied after convolution layer. An activation function allows a size of input as Winput X Hinput X Dinput and fire on activation function then the size of the output features after activation function is same as previous layers.

Pooling layer:

Pooling layer used to reduce the computation of CPU choosing stride is very important for Pooling the value S>1 helps to reduce the size. The main purpose of the Pooling layer is to reduce the time domain image size progressively. Because of this input volume size was reduced and number of parameters and computation also reduced.

$$W_{output} = ((W_{input}\text{-}F)/S) + 1$$
$$H_{output} = ((H_{input}\text{-}F)/S) + 1$$
$$D_{output} = D_{input}$$

Fully connected layer:

This layer works is helpful for flatten 3-D size matrix to 1-D size matrix in the defined work [15], after flatten layer the size of array obtained is 6272.

Dense:

At final unit dense was fully attached to every neuron consisting of a squashing function as activation because our problem to detecting a tumor. If the output of layer is zero then it indicates non-tumorous Image. If the output of dense is 1 then it indicates Tumor MRI.

III. RESULTS

In the experiment we used total 2065 images 47% of them are no tumor and 53% are tumor images. After completion of the training to the model we get accuracy on the validation data set is 91% which is more than the models proposed by brain tumor "Detection Using Deep Learning Model" Sneha Grampurohit et. al. they claimed their accuracy on the validation data set is 86%. The simulation results are shown in fig 15 and fig 16.

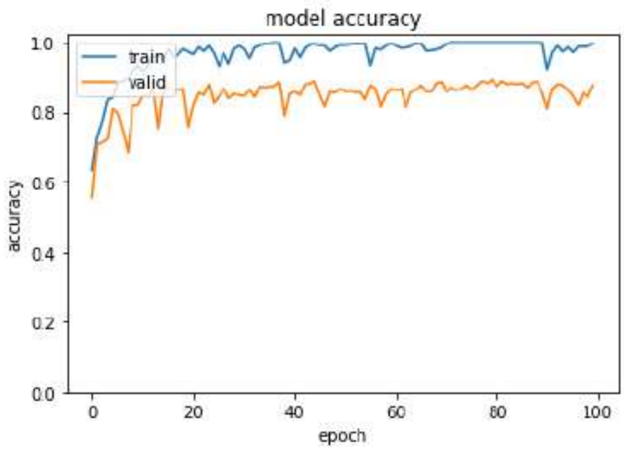


Fig 15. Accuracy chart

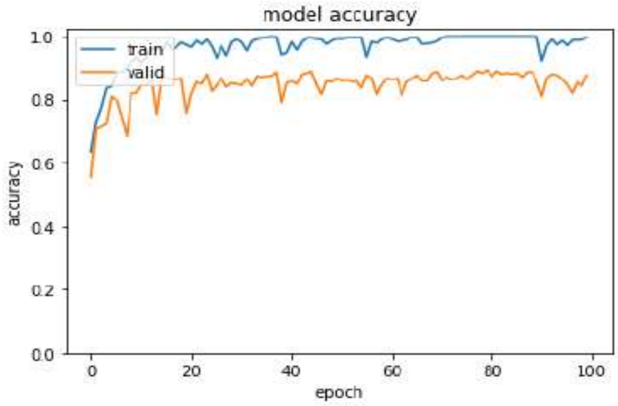


Fig. 16. Accuracy on test data.

IV. CONCLUSION

In the proposed model the validation accuracy is 91% which is more than the models proposed by the previous works which is only 86% by "Detection Using Deep Learning Model" Sneha Grampurohit et. Al [16], and the model "Brain tumor type classification via capsule networks" by parinan et. al. [17] was gives only the accuracy of 86.56%. VGG16 also we compared in this work VGG16 model depth is very high and the number of learnable parameters also more when compared to the proposed model.

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