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Detection of Brain Tumour by integration of VGG-16 and CNN Model

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Abstract: Medical science has incredibly succeeded and grew to become excellent in modern years. Technology is altering the world of medicine. Numerous upgrades and new preferences are already in the market and they all elevated fitness care drastically. But human beings, flip out to be scared when they hear cancer. The main objective of our project is to detect the brain cancer by using Convolutional Neural Network(CNN) and VGG16. A Convolutional Neural Network is a classification of deep neural networks, most often utilized to analyse visual imagery. CNN is now the go-to model on every image associated problem. The principal gain of CNN model is it mechanically sense the essential feature barring human supervision. There are many CNN models are there like VGG-16,ResNet model. Amongst the nice performing CNN models, VGG is terrific for its simplicity. VGG-16 incorporates sixteen layers, a crucial CNN model comes to the notion if one wishes to use an off-the-shelf model for a task. Our paper intends to locate out the brain tumour with the utilization of VGG-16, Convolutional Neural Network model architecture and weights train the model for this problem. The performance will be evaluated on accuracy. The information set we desire to use in our work is Brain MRI images for Brain Tumour Detection.

***Index Terms*: Convolutional Neural Network(CNN), VGG-16,Accuracy, Classification**

I. Introduction

Science is understanding and discovery of nature where as Engineering is manipulating the forces of nature to enhance humanity. Science is built to research where as Engineering is learned to build[1]. Information Technology performs as essential role in our current lifestyle. Artificial Intelligence comes under the domain of science co-operated with the idea of designing a machine which can learn by itself without any person's interference. Because of ML, humans can design machines which can think like humans and can learn from the experiences like human do [2]. Many of the practical examples we are seeing today like solving various optimization complications, classifying huge digitized data and getting required pattern, self-driving cars depending on natural language processing and deep learning [3-5]. The subunit of machine learning is deep learning in which the information is fed into deep learning model and it routinely learns by capacity of itself besides any human interference [6]. Deep Learning is utilized for social community filtering, fraud detection [7]. The existence of more layers and model is deeper, then the overall performance will be higher. Different deep learning algorithms are Multilayer Preceptron Neural Network, Convolutional Neural Network, Recurrent Neural Network, long Short-term Memory, Deep Boltzmann Machine(DBM), Deep Belief Networks to function on sequential Data(signals and text), Recurrent Neural Networks are there. MLPNN is a fully connected neural network and makes use to feed forward supervised learning algorithm. MLPNN is viewed as inadequate for modern-day superior computer vision tasks [8-9]. MLPNN is inefficient due to the truth redundancy in such dimensions. Here we need to feature these deep learning algorithms on image data. So, selecting Convolutional Neural Networks will required results [10-11]. A group of uncommon, extraordinary cells is tumour.

Growth of these cells internal mind is recognized as Brain Tumour. Te Scalp covers human mind might also be very rigid. So, any enlarge of such uncommon cells can purpose problems. When tumour cells develop inner the human mind, there are chances of causing the pressure internally the mind ends in human demise sometimes. That's why mind tumours are very unstable and life-threatening [12]. Still no one is aware of the real purpose in the black of the occurrence of these tumours. Though we don't understand the cause for a brain tumour, we can perceive the tumours with the help of symptoms. Different forms of tumours are there and have wonderful treatments. Two categories of brain tumours are presently names as primary and metastatic mind tumours [13]. The in advance originate within the mind and can enhance form super cells of abilities and the later starts in the brain and slowly spread from the brain to the other components of the body. Brain tumours have distinct shapes, top-notch dimensions and can appear at different locations within the mind. Some tumours can affect encircling structures. So earlier than going to do brain surgical procedures or any treatments, there is a need for medical doctors to discover the precise location, boundaries and regions of the brain tumour. The work of brain tumour segmentation is to separate tumour affected areas from healthy tissues. Hence brain tumour segmentation is the toughest task in clinical diagnosis [14]. X-ray, MRI are some of the scientific imaging techniques available. The utilization of MRI snap photographs is beneficial because it has great resolution. MRI image has an incredible quality which performs an indispensable role in figuring out the specific affected region. Because now, most of the strategies are based completely on human experience which may additionally lead to the false identification of the tumours.

- We developed a CNN model to detect whether a person is having brain tumour or not.
- For this problem, we used VGG-16 model architecture and weights to train the neural network model.
- We used Brain MRI Images in the entire process for training and testing the model, MRI images are collected from Kaggle.
- We evaluated the performance of our CNN model in terms of Accuracy.

The subsequent sections are organized as follows: Section 2 represents the literature review. Section 3 represents basic preliminaries and section 4 represents materials and methods includes dataset description, section 5 represents proposed work includes the workflow of our project includes pre-processing, normalisation, and data augmentation and result analysis. Section 6 is the conclusion and then finally the reference section.

II. Literature Review

The more than a few strategies of brain tumour detection and segmentation have been cited as follows. Cui (2018) developed a novel automated segmentation primarily based on cascaded deep learning Convolutional neural network. It has two sub networks. Localization Network (TLN) and an intra tumour classification network (ITCN). The tumour area from the MRI brain slice is separated by the usage of tumour localization network. ITCN helps to label the defined tumour area into a couple of sub-regions. The dataset used was BRATS dataset. The evaluation can be performed through sensitivity [15]. Khawaldeh (2018) given machine learning method for medical image classification and segmentation. The method uses Convolutional networks for classifying brain clinical images. It classifies the brain tumour into excessive and low grades [16]. Haveri (2017) defined segmentation of brain tumour using deep neural networks to classify tumour into low and high grades. This article makes use of the Convolutional neural networks as a machine learning algorithm. The dataset used to be BRATS dataset. Dong (2017) proposed non-invasive magnetic resonance methods as a diagnostic tool to discover brain tumour barring ionizing radiation. The network used in this task was u-net based deep convolution network. It presents the most beneficial outcomes for the core tumour regions [17]. Hussain (2017) recommended a segmentation algorithm to discover the gliomas-based brain tumour. It makes use of deep convolutional neural network algorithm to detect the tumour which has an irregular shape. Hence, the recovery chances of the affected person are increased with correct segmentation of brain tumour. The trouble of overfitting is removed by means of introducing max-out and drop out layers in the patch processing. This proposed algorithm additionally makes use of a pre-processing method to put off the undesirable noise and post processing helps to take away small false positive using morphological the data set used to be BRATS 2013[18]. Chinmayi (2017) conferred an approach for MRI brain tumour segmentation and classification using Bhattacharya co-efficient. The unwanted skull parts have been eliminated with the usage of anisotropic diffusion filter. Fast-bounding box algorithm has been used to extract the tumour area. It uses deep learning CNN to train the MRI brain tumour image. Finally, the consequences of the proposed method compared in terms of accuracy. The outcomes will assist the radiologist to identify the size and position of a tumour. Kamnitsas (2017) developed a segmentation of brain lesion which is a challenging mission performed using the three-D convolutional network. The twin pathway structure was used to extract the nearby and large contextual information, which operates an input image at multiple scales. The false positives which were eliminated by using 3D fully connected conditional random field. The segmentation procedure was used to separate lesion on multi-channel MRI with traumatic brain injuries, brain tumours and ischaemic stroke. The 3D CNN is a high-quality method, which affords suitable segmentation barring increasing the computational cost and the wide variety of training parameters [19]. Isil (2016) mentioned that segmentation of brain tumour us one of the challenging tasks in medical field. The lifetime of the patient is expanded by using early prognosis of brain tumour. Manual segmentation of brain tumour for huge amount of data is a painstaking process. Hence there is a need for automated segmentation. Now a days the automatic segmentation uses deep learning strategies for segmentation. It gives efficient segmentation for a massive amount of MRI based photograph data. The article reviewed the present-day methods of deep learning. Pereira (2016) described gliomas is one of the aggressive kinds of brain tumour which leads to the short lifetime with their best grade. The automated brain tumour segmentation is one of the difficult tasks due to the large, spatial and structural variability amongst brain. The writer recommended a new segmentation technique primarily based on a Convolutional neural network with small 3×3 kernels. The small kernel helps the deep architecture to keep away from over fitting by way of assigning the fewer range of weights in the network and using intensity normalization as a pre-processing approach along with CNN presents high-quality segmentation. The proposed work is carried out BRATS 2013 database [20]. Wang (2017) endorsed that Convolutional neural network gives the state-of-the-art performance for automated medical segmentation. But it failed in giving sturdy outcomes for medical use. The trouble is rectified by using novel deep learning based interactive segmentation framework. The proposed approach makes the CNN model adaptive to a specific test image, which can also be supervised or unsupervised [21].

III. Basic Preliminaries

This section gives the detailed explanation of the Convolutional neural networks.

A. Neural Networks

Neural Networks are the networks in which a computer analyse to operate a task through analysing training examples. When CNN is trained, training information is fed to the input layer, i.e., the backside layer of neural networks and it goes to the output layer by way of passing via the subsequent layers. If an image with 200×200×3 pixels is taken and feed it to a fully connected network, no. of weights will be 120000 lead to overfitting. So, we can't use fully connected networks for image classification for large datasets. In realistic world, the images are no longer that small, and we must deal with such large quantity of data. In CNN, the neuron in the layer is linked to a small area of layer before it instead of all neurons as in a fully connected network.

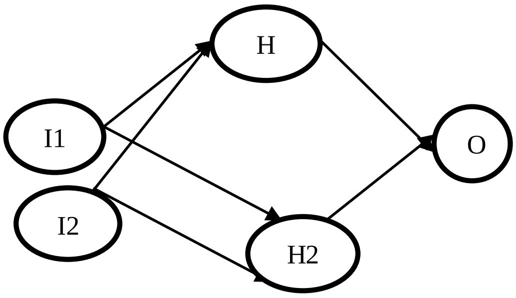


Fig. 1 Basic Architecture of Neural Network

The figure represents the neural network which consists of 2 inputs, two hidden layers and finally one output layer.

$\mathrm{O(1) = W(1)X + b(1)}$ (1)

$\mathrm{a(1) = O(1)}$ (2)

Layer 2:- 2 is output from layer1

$\mathrm{O(2) = W(2) * a(1) + b(2)}$

$\mathrm{a(2) = O(2)}$ final calculation

Substituting $\mathrm{O(1)}$ value here

$\mathrm{O(2) = \left[W(2) * \left(W(1)X + b(1)\right)\right] + b(2)}$

$\mathrm{O(2) = [(W(2) * W(1) * X) + \left(W(2) * b(1) + b(2)\right)]}$

Let $\mathrm{W = W(2) * W(1)}$ (3)

And $\mathrm{b = (W(2) * b(1) + b(2))}$ (4)

From Eq. 3 and 4, final output can be computed as:

$\mathrm{O(2) = W * X + b}$

The conclusion is no matter how many hidden layers we use in neural net, all layers behave in same manner. So it's important to pick the correct activation function. One general activation function is being used mostly nowadays is ReLu activation function. We can use ReLu activation function to any neural net if one is unaware of the remaining activation functions. For any binary classification, sigmoid function is natural pick for output layer. ReLu activation function is also popular as Rectified Linear Unit. It is applied in hidden layers of neural network. Range is [0, inf). Benefits are less expensive and efficient and easy for mathematical computations

$$R(z) = \max(0, z)$$

B.Outline of CNN

Pattern detection makes CNN helpful for image analysis. CNN has hidden layers referred to as Convolutional layers. Convolutional layer receives input and then transforms the input and then send it to the subsequent layer referred to as convolution operation. Convolutional layers detect the patterns. These layers have some variety of filters which performs a predominant role in pattern detection. Patterns that filter ought to detect the edges, circles and so forth in an image. Filters can additionally be successful to detect specific objects. We should specify number of filters we decide for the convolution layer to have.

Filter is a small matrix which contains number of rows and columns. The dimension of a filter is 3×3. When Convolutional layer get input, the filter is going to convolve during each 3×3 block of pixels from input

Table 1 Convolutional Neural Networks used in Medical field: literature survey

References	Neural Network	Specialization	Year
Cui, S[15]	Deep cascaded neural network	Automatic segmentation of glioma tumour	2018
Khawaldeh, S[16]	CNN	Non-invasive grading of glioma tumour	2018
Dong, H [17]	u-net based fully convolutional networks	Automatic brain tumour segmentation	2017
Hussain, S [18]	Cascaded deep convolutional neural network	Brain Tumour Segmentation	2017
Kamnitsas, K[19]	Multi scale 3D CNN	Brain lesion segmentation	2017
Pereira, S [20]	CNN	Brain Tumour segmentation	2016

- Fully Connected Networks are less efficient compared to CNN
- Each neuron in CNN is connected to neurons in the previous layers but not in fully connected networks
- CNN is cheap in the terms of memory and power compared to fully connected networks.

IV. Materials and Methods

In this paper we used Convolutional Neural Networks for the detection of the brain tumour and performance was evaluated based on the accuracy of the model performance. The information set used for this problem is MRI brain images. There are 2 folders in this dataset. Yes folder and No folder. Yes folder is a folder which contains tumorous MRI images. Total tumorous images in Yes folder are 153.No folder contains 98 non tumorous MRI images. We split the data set into 3 sets. They are 1. Training set 2. Testing set 3. Validation set. Training set is the set which is used to train the model. Validation set is the set which is used during the training to know whether it can cause overfitting or not. The final and the most important set is test set which is a separate set which is not seen by the model and is used to evaluate the accuracy of performance of the model. We can split the data in the following way

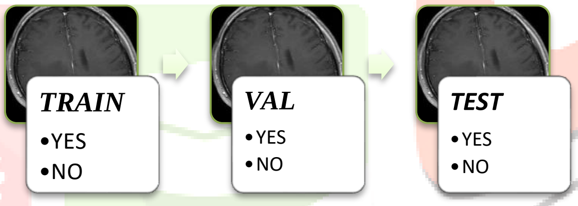


Fig. 2 splitting of datasets

Many researchers do detection of brain tumour using programming tools like MATLAB. . But we chose python programming to implement our project work. Some of the reasons behind the implementations of our work using python are:

- MATLAB data structure is inferior to Python
- Python is open source and provides more datasets and graphic packages.
- Python code is readable and more concise than MATLAB.
- Python provides more control over the code organization and obviously it has better name space management.
- We can easily maintain multiple versions of shared libraries.

V. Proposed workflow

This section presents the work flow our proposed work in detail. We worked on how to detect brain tumour using VGG-16 model and performance evaluated in terms of accuracy.

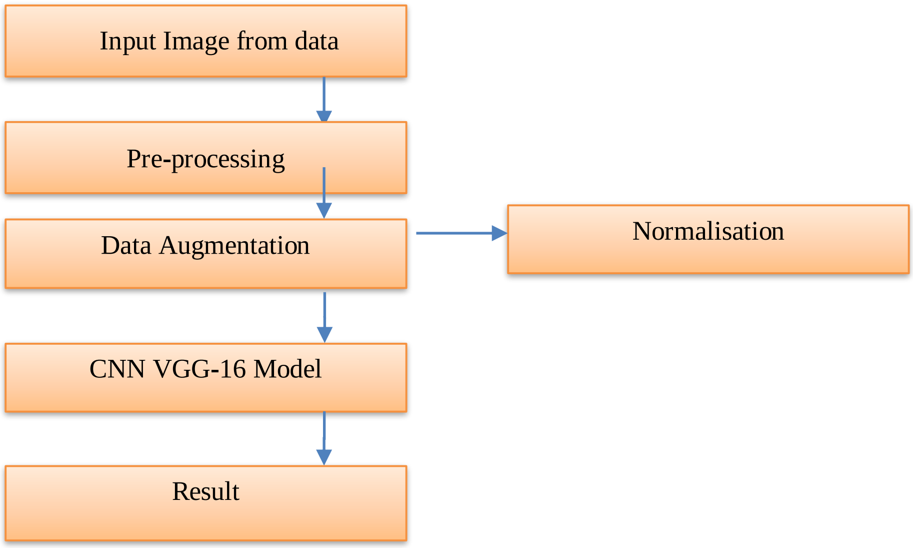


Fig.3 Workflow of the proposed model

A.Pre-processing

The next step will be resizing images in the data set to (224×224) and applying pre-processing techniques on the images which are needed as an input for the VGG-16 model. Pre-processing is applied for each image in the data set. The first step we need to do is normalization. Firstly, we need to crop the brain from the images. Normalization is the technique of pre-processing. Step wise explanation of how pre-processing done.

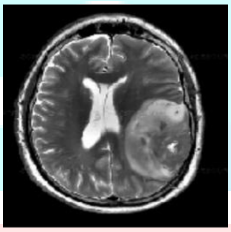


Fig. 4 Input image

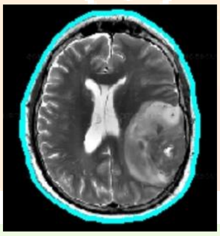


Fig. 5

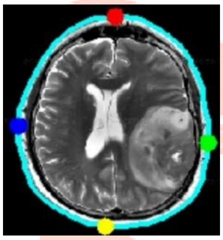


Fig. 6

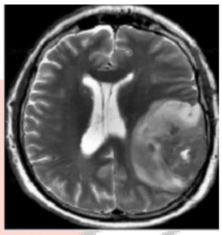


Fig.7

In the above picture Fig. 5 represents the input image need to be pre-processed and fig 2. Represents the second step of pre-processing in which we need to find the highest contour. Now we need to identify here the edges of the brain. Fig. 6 represents the extreme points we need to identify to crop the brain out of the image carefully. Fig. 7 is the desired pre-processed image.

B.Data Augmentation

Data Augmentation is one of the pre-processing techniques need to use on the data set. We apply data augmentation because the data set is small and need to increase the size of the data set. Then we will have enough examples to train the model. It will reduce the data imbalance in the data.

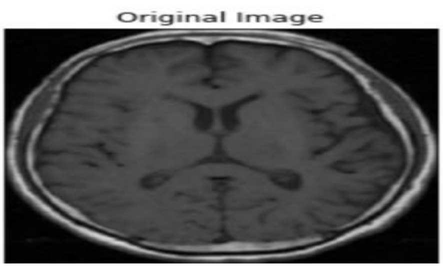


Fig 8. Original Image

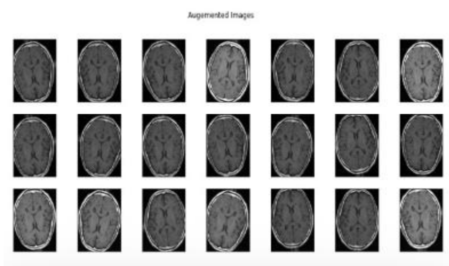
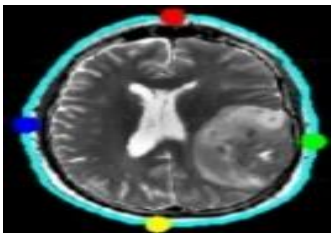


Fig. 9 Data set after data augmentation

This is how the data set look like after the data augmentation. From fig.9 we can observe the augmented images. After the data augmentation, our data size became 253 and train data is 177 and test data is 76. Remaining images are come under validation data.

C.Normalisation

Initially we need to import an OpenCV package and with the help of that package, we implement cv2. Threshold, cv2.dilate functions. Dilate and Erosion are mostly used morphological operators perform morphological operations. These operations work on images based on image structure.



By implementing above functions, the original image converts into grey and the small noisy data removed. By using cv2. Find contour method we will get highest contour area. The desired image will be like a matrix, with coordinates (x, y).

- The most important benefit is used to remove noise
- Another benefit is, identifying intensity bumps or holes in an image.

D.Vgg-16

Vgg-16 is a type of convolutional neural network architecture which has 16 layers. It is popular as one of the brilliant vision model architecture till day. The uniqueness of VGG-16 model architecture is instead of having more parameters, focuses on convolution layer of 3x3 kernel size. The importance of this model is its weights are freely available on the internet and can be downloaded to use in own models and application. It is known for its simplicity compared to other model architectures. This model's minimum input image size expectation is 224x224 pixels with 3 channels. The benefit of having small size kernels is the problem of overfitting can be avoided. Activation functions is used in neural network to decide if neuron should be activated or not by calculating the weighted sum of input. The need of activation functions is to bring non-linearity into the neuron's output. Neural Network contains neurons that work in coordination with weight, bias, and respective activation function. The updating of weights and biases of the neurons are done depending on the error at the output. Activation function bring non-linearity to the input of neural nets and allow it to learn and perform complex tasks.

E.Result Analysis

In our proposed work, our main motive is to develop a model which has a good fit and to avoid under fit and over fit problem. From the result we analysed that our model did not cause overfitting and underfitting problem. The model loss should always be lesser in training data compared to test data. We observed that if we chose neural nets for solving classification problems, beneficial to use deep learning frameworks like tensor flow and keras.

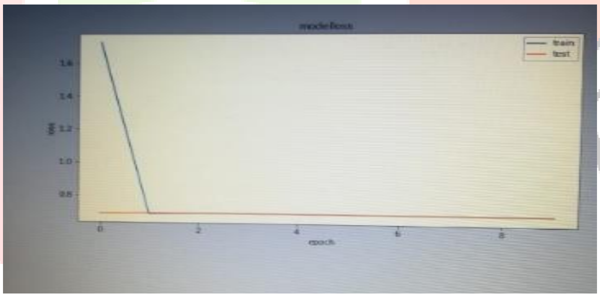


Fig 10. Output curve

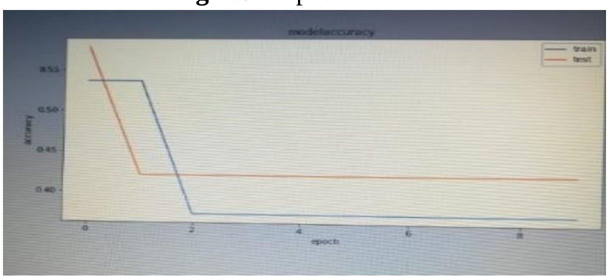


Fig 11. Output curve

The benefit is, if we learn these operating concepts and can able to understand these learning curves, neural nets can solve even complex problems. The model loss should always be lesser in training data compared to test data. We observed that if we chose neural nets for solving classification problems, beneficial to use deep learning frameworks like tensor flow and keras. The benefit is if we learn these operating concepts and can able to understand these learning curves, neural nets can solve even complex problems. We can use these powerful tuning options to prevent fitting problems. The gap between train and test loss learning curves is called generalisation gap. The orange line and blue line indicates the test and train accuracy.

$$Accuracy = \frac{Number\ of\ correctly\ predictedimages}{Total\ number\ of\ images} \times 100$$

We used two classes and we calculated accuracy using the above formula. Our model reached 84% accuracy and the accuracy of our model will increase by increasing number of trained images and tuning hyper parameters.

VI. Conclusion

Deep Learning is changing the vision of humans towards technology. There is divination that deep learning is already making an impact on people's lives, giving brilliant outcomes in the medical field, its applications will affect in future generations and will make impact beyond expectations. The scope of this Machine learning subset is very high due to its ability to face wide variety of problems and win the competition in the future. In coming 5 years, tools of deep learning will get a standard place in developer's tool kit. There are so many deep learning applications is in the market and there is no doubt in saying that the applications of deep learning will rule the world and will leave a huge impact. With the use of CNN we can do wonders in the medical field and can save people's lives. Our work is a combination of Convolutional Neural Network model to predict whether the subject has brain tumour or not and computer vision problem to automate the process of cropping brain from MRI scans. CNN gives better accuracy and boosts the system's performance. CNN is better than remaining deep learning networks. Hope this paper gave a better practical understanding of how CNN models can give accurate results and motivate to use CNN in medical fields. On the other hand, scope of Deep Learning is very huge in future because of its ability to solve itself and can learn by model itself without any human interference. Another most important feature is it performs very well on the raw data i.e., images.

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