JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Brain Tumour Detection by Convolutional Neural Network

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Abstract A brain tumour is a collection, or mass, of abnormal cells inside the brain. The skull encloses the brain, and is very strong. Any growth inside such a space can create problems. Brain tumours can be of two types i.e. cancerous (malignant) or non cancerous (benign). Brain cancer is a life-threatening disease and it affects all the diagnosed people severely. Precise brain tumour classification helps to diagnose brain cancer early, which increases the survival rate of brain cancer patients, but it is quite hard to detect early. It is difficult to evaluate the magnetic resonance imaging images manually. Therefore there is a need for optimised and fast digital methods for tumour diagnosis with better accuracy. This paper also details the different machine learning techniques used to classify cancer into malignant and normal category. We have used two activations functions and compare the accuracy. We get the highest accuracy on relu which is 91.23% on 100 epochs.

Keywords— Convolutional Neural Network, Deep Learning, Image processing

I. Introduction

A brain tumour is an abnormal mass of tissue inside the skull in which cells grow, multiply uncontrollably and invade healthy brain tissue nearby. There are two main types of brain tumours: malignant (cancerous) and benign (non cancerous). Brain tumours that begin inside the brain are called primary brain tumours and cancers that begin in other parts of the body and spread to the brain are called secondary (metastatic) brain tumours. The growth rate of brain tumours varies greatly. The growth rate and location of a brain tumour determine how they affect the functioning of the nervous system. Treatment options for brain tumours depend on the type of brain tumour and its size and location. Signs and symptoms of brain tumours vary widely, depending on the size, location, and growth rate of the brain tumour. Common signs and symptoms caused by brain tumours include altered patterns of headaches, gradually frequent and severe headaches, unexplained nausea and vom- iting, visual impairment such as arm and leg movements, and balance disorders. **[1]**

According to the National Brain tumour Society, there are more than 120 types of brain tumours. Some brain tumours, such as glioblastoma multiforme, are malignant and can grow rapidly. Other types of brain tumours like meningiomas grow slowly and are called benign. The most common primary brain tumours are called gliomas and are derived from glial tissue (supporting tissue). About one-third of all primary brain tumours and other tumours of the nervous system originate from glial cells. More than half of all gliomas diagnosed in adults are glioblastoma, a highly aggressive type of brain tumour. Glioblastoma is the most common type of grade 4 brain cancer. Glioblastomas can develop in any lobe of the brain, but they are more common in the frontal and temporal lobes. Adults are most commonly affected by glioblastomas. Meningioma is a type of cancer that develops in the cells that line the membrane that surrounds the brain and spinal cord. Meningiomas (also known as meningeal tumours) make up around a quarter of all intracranial tumours. The majority of these tumours are harmless (non-cancerous and slow- growing). Surgery is usually used to remove meningiomas. Some meningiomas might not require treatment right away and can go unnoticed for years. Pituitary tumours are masses that form in the pituitary gland, a tiny gland the size of a pea that resides just below the brain and above the nasal passages inside the skull. Pituitary tumours, also known as pituitary carcinomas, are extremely rare; according to the American Cancer Society, just a few hundred have been documented in the United States.**[2]**

The 5 year survival rate indicates the percentage of people who are alive at least 5 years after the tumour is found. The 5 year survival rate for people in the United States with cancerous brain or CNS tumours is almost 36% and is almost 31% for the 10-year survival rate. Cancer is one of the leading causes of death in the world, with approximately 10 million or1 in 6 deaths in 2020. In 2022, a total of 1.9 million new cancer cases and 609,360 cancer deaths are expected in the United States, which is equivalent to approximately 1,670 deaths per day. **[3]**

Survival of brain tumour patients depends on many factors such as type of tumour, grade of tumour, position in the brain, size or shape of the brain tumour, age at diagnosis. In general, fast-growing (high-grade) tumours are much more likely to come back after treatment than slow-growing (low- grade) tumours. Surgery of tumours for some parts of the brains is quite difficult like tumours near the nerves that control sight, spinal cord etc. For some areas surgery is not an option for these areas doctors use radiotherapy or chemotherapy. Large tumours or tumours with unclear boundaries can bemore difficult to remove. **[4]**

II. Literature Survey

Hossam H. Sultan, Nancy M. Salem, and Walid Al-Atabany **[6]** suggested a DL model, using two publicly available datasets based on a CNN to categorise distinct brain tumour types. The first divides tumours into categories (meningioma, glioma, and pituitary tumour). The other distinguishes betweenthree types of glioma (Grade II, Grade III, and Grade IV). For the two studies, the suggested network has the best accuracyof 96.13 % and 98.7 %, respectively.

Chirodip Lodh Choudhury, Brojo Kishore Mishra, Chan- drakanta Mahanty, and Raghvendra Kumar **[7]** devised a deep learning based CNN method that distinguishes between tumorous and non-tumorous brain MRI images. This is ac- complished by utilising a three-layer CNN to extract features, followed by a fully connected network with 35 epochs toclassify the data. In 35 epochs, the model obtained a training accuracy of 97.47 %.

Arshia Rehman, Saeeda Naz, Muhammad Imran Razzak, **[8]**, Here three convolutional neural network architectures (AlexNet, GoogLeNet, and VGGNet) are used to categorise brain tumours like meningioma, glioma, and pituitary in the suggested framework. Using the fine-tune VGG16 network, they were able to achieve the greatest accuracy of 98.69 % of all the studies.

Francisco, Mario, M´ıriam and David presented **[9]** a fully automatic brain tumour segmentation and classification method, based on a CNN (Convolutional Neural Network) architecture designed for multiscale processing. They evalu- ated its performance using a publicly available T1-weighted

contrast-enhanced MRI images dataset. This method obtained the highest tumour classification accuracy with 97.3 %. Muhammad Sajjad, Salman Khan, Khan Muhammad, Wan- qing Wu, Amin Ullah, Sung Wook Baik presented **[10]**, Their system is threefold: 1) the tumour regions from the datasetare segmented through a CNN model, 2) the segmented datais further augmented using several parameters to increase the number of data samples, and 3) a pre-trained VGG-19 CNN model is fine-tuned for multi grade brain tumour classification. They improved the accuracy by utilising data augmentation. Materials and Methods

A. Proposed Methodology

In a proposed system, we are proposing an experiment on brain tumor disease with a limited set of supervised data. We are proposing a combination of a Convolutional neural network-based multimodal disease risk prediction model with higher accuracy. We are going to solve the accuracy issue in the diagnosis of lung cancer with accurate stage predictions.

B. Dataset

We have collected the dataset from kaggle platform. We have split the dataset into two categories training and testing. For training 300 images and testing 60 images we are used.

C. Pre-processing

In pre-processing we are convert the every image into 224*224.

D. Data augmentation

In data augmentation we are simply increase the dataset of training directory. We generate every image different format such as rotation, zoom and change the brightness of image.

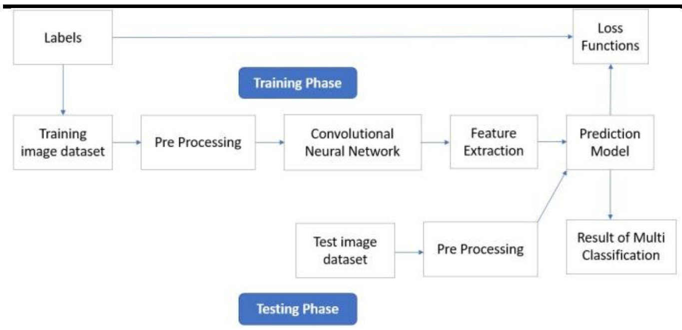

Figure 1: Architecture Diagram

E. Algorithms

1) Convolutional Neural Networks (CNN)

Convolutional Neural Networks (which are additionally called CNN/ConvNets) is a kind of Artificial Neural Networks that are known to be tremendously strong in the field of distinguishing proof just as picture order.

Four main operations in the Convolutional Neural Networks are shown in figure2.

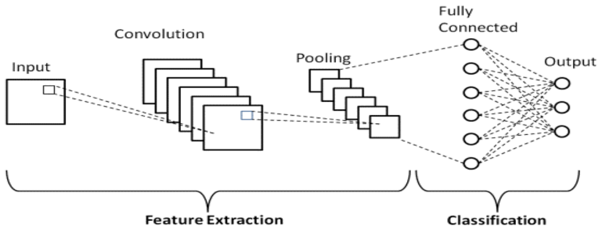

Figure 2: Architecture of CNN

i) Convolution

This layer is the first layer that is used to extract the various features from the input images. Here, the mathematical operation of convolution is performed between the input image and a filter of a particular size MxM. By sliding the filter over the input image, the dot product is taken between the filter and the parts of the input image with respect to the size of the filter (MxM).

The output is termed the Feature map which gives us information about the image such as the corners and edges. Later, this feature map is fed to other layers to learn several other input image features.

(ii)Activation Functions:

1. Rectified Linear Unit (Relu)

ReLU follows up on a rudimentary level. All in all, it is an activity which is applied per pixel and overrides every one of the non-positive upsides of every pixel in the component map by nothing.

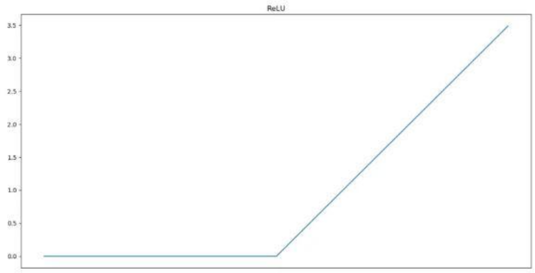

Figure3: Relu Activation

It is represented as:

$$f(x) = \begin{cases} 0, & if\ x<0 \\ x, & otherwise \end{cases} \ \dots\dots\dots\dots (1)$$

2. Sigmoid

As you can see in the figure4, the function slowly increases over time, but the greatest increase can be found around x=0. The range of the function is (0,1); i.e. towards high values for x the function therefore approaches 1, but never equals it.

It is represented by

$$y: f(x) = \frac{1}{1+e-x} \dots\dots\dots\dots (1)$$

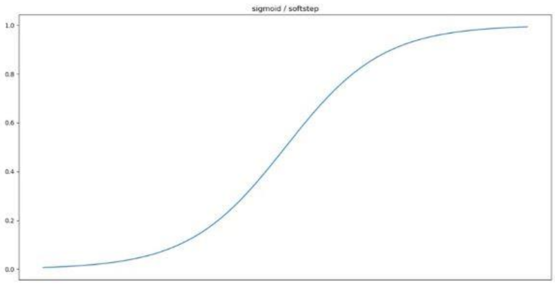

Figure 4: Sigmoid Activation

iii). Pooling or sub-sampling

Spatial Pooling which is likewise called sub-sampling or downsampling helps in lessening the elements of each element map yet even at the same time, holds the most important data of the guide. Subsequent to pooling is done, in the long run, our 3D element map is changed over to a one-dimensional component vector.

iv) Fully connected

Neurons in layers are fully connected to all activations in the previous layer, as is the standard for feedforward neural networks. Fully Connected layers are always placed at the end of the network.

III. Results and Discussion

Learning model is partially implemented. It is trained for 2 classes. For training and testing purpose total 360 images are used per class. Out of which 300 images are used for training dataset and 60 images are used for testing dataset. So 80% and 20% distribution is used for training and testing dataset respectively. Images are resized to 224*224 matrix and used as input to CNN.

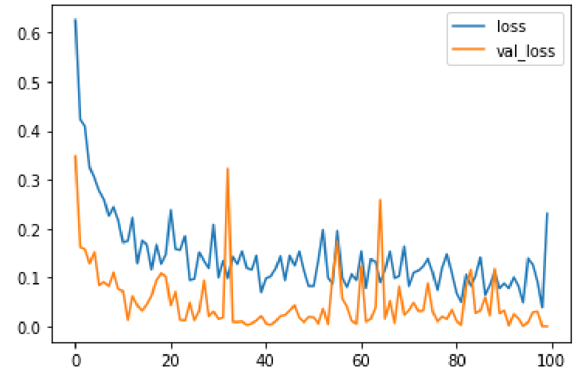

Figure5: Model Loss

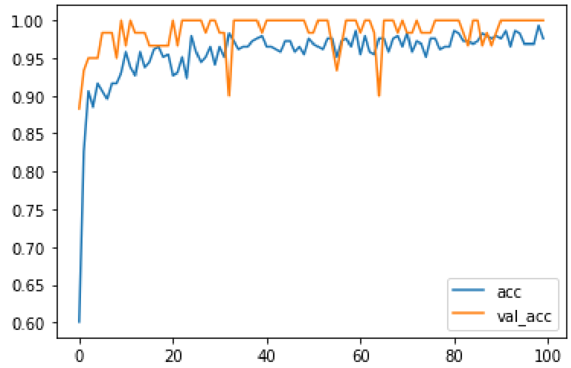

Figure6: Model Accuracy

Activations	Train	Test	Accuracy
Sigmoid	300	60	42.86
Relu	300	60	91.23

Table1: Comparative Analysis

Once the CNN is trained with features of the training dataset, it performs the process of feature extraction in appropriate manner. The output of this trained CNN model which performs the classification process. The recognized class with the uploaded images. Batch size for training and testing are kept as 206 and 100 respectively. Training and testing accuracy of model for 100 epochs is shown in figure 5 and figure6. It is observed that accuracy increases with number of epochs. In this paper we have compare the results with two activation functions like sigmoid and Relu. But Relu gives the better accuracy as compare to sigmoid as shown in Table1. The speed of building models based off on ReLU is very fast opposed to using Sigmoid activation function.

IV. CONCLUSION

We are going to invent brain tumor disease detection system over machine learning and CNN techniques which solves existing accuracy problem as well as reduce death rates by diseases like brain tumor. In this paper we are comparing the accuracy by two activation functions. We get the highest accuracy on relu activation function. For future work, we can implement this technique on some more diseases with rich dataset. Increasing the number of diseases and dataset used for the process can improve the accuracy.

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