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Brain Tumor Detection Using Deep Neural Networks

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ABSTRACT

Brain tumor is one of the major causes of death among other types of the cancers. Proper and timely diagnosis can prevent the life of a person to some extent. Therefore, this work is proposed for an automated reliable system for the diagnosis of the brain tumor. In our Project we are using a deep learning technique called Deep Convolutional Neural Network to detect the Brain Tumor. By Using this algorithm, we can able to get the accuracy of above 90% during training and testing.

Keywords: CT Scan, MRI Scan, Deep Learning,CNN.

INTRODUCTION

A brain tumor occurs when abnormal cells form within the brain. There are two main types of tumors: cancerous (malignant) tumors and benign (non-cancerous) tumors. Cancerous tumors can be divided into primary tumors, which start within the brain, and secondary tumors, which most commonly have spread from tumors located outside the brain, known as brain metastasis tumors. All types of brain tumors may produce symptoms that vary depending on the part of the brain involved. These symptoms may include headaches, seizures, problems with vision, vomiting and mental changes. The headache is classically worse in the morning and goes away with vomiting. Other symptoms may include difficulty walking, speaking or with sensations. As the disease progresses, unconsciousness may occur.

The cause of most brain tumors is unknown. Uncommon risk factors include exposure to vinyl chloride, Epstein–Barr virus, ionizing radiation, and inherited syndromes such as neurofibromatosis, tuberous sclerosis, and von Hippel-Lindau Disease. Studies on mobile phone exposure have not shown a clear risk.

The most common types of primary tumors in adults are meningiomas (usually benign) and astrocytoma's such as glioblastomas. In children, the most common type is a malignant medulla blastoma. Diagnosis is usually by medical examination along with computed tomography (CT) or magnetic resonance imaging (MRI).[2] The result is then often confirmed by a biopsy. Based on the findings, the tumors are divided into different grades of severity. Treatment may include some combination of surgery, radiation therapy and chemotherapy. If seizures occur, anticonvulsant medication may be needed. Dexamethasone and furosemide are medications that may be used to decrease swelling around the tumor. Some tumors grow gradually, requiring only monitoring and possibly needing no further intervention. Treatments that use a person's immune system are being studied. Outcome varies considerably depending on the type of tumor and how far it has spread at diagnosis. Although benign tumors only grow in one area, they may still be life-threatening due to their location. Glioblastomas usually have very poor outcomes, while meningiomas usually have good outcomes.[3] The average five-year survival rate for all brain cancers in the United States is 33%.

Secondary, or metastatic, brain tumors are about four times as common as primary brain tumors, with about half of metastases coming from lung cancer. Primary brain tumors occur in around 250,000 people a year globally, making up less than 2% of cancers. In children younger than 15, brain tumors are second only to acute lymphoblastic leukemia as the most common form of cancer. In Australia, the average lifetime economic cost of a case of brain cancer is $1.9 million, the greatest of any type of cancer.

OBJECTIVE

The main objectives of this project are:

- To design and implement a brain tumor detection system using Deep Convolutional Neural Network.
- To provide quick result for the tumor affected persons.
- To achieve more comfort for both doctors and patients.

EXISTING SYSTEM

In the existing system they used a Fully Automatic Heterogeneous Segmentation using Support Vector Machine (FAHS-SVM) for brain tumour classification. Although it gives a maximum accuracy of above 90% during validation when we increase the dataset for validation purpose it will suddenly drops down. This is the problem statement present in existing system.

PROPOSED SYSTEM

In the proposed system we use a deep learning method which is called as Convolutional Neural network (CNN) to classify the given Brain MRI Image whether it is a normal image or tumour detected MRI. We use Deep Convolutional neural network (DCNN) algorithm. This model will provide an accuracy of above 90% during validation and testing.

LIST OF MODULES

- Dataset Collection
- Pre-processing
- Training
- Testing

Dataset collection:

In our project we have totally 510 images, in that 510, 400 images are used for Training purpose and 110 images are used for validation purpose. In that 400 image files 200 images are Tumor +ve images and remaining 200 images represents Tumor –ve images.

Pre-processing:

At first these 400 images are pre-processed by using pre-processing techniques such as zooming, shearing, rescaling and horizontal flipping. A pre-processing or filtering step is applied to minimize the degradation related to the noise. This stage is necessary to enhance the lungs image quality and made the feature extraction component more reliable for the improvement of broad and narrow input image.

Training:

In training, we use Deep convolutional neural network algorithm. Each input image will pass it through a series of convolution layers with filters. In order to perceive the same as humans, CNNs have digital colour images that have red-blue-green (RGB) encoding. There is a Convolutional Layer, Activation Layer, Pooling Layer, and Fully Connected Layer, these are all interconnected so that CNNs can process and perceive data in order to classify images.

Testing:

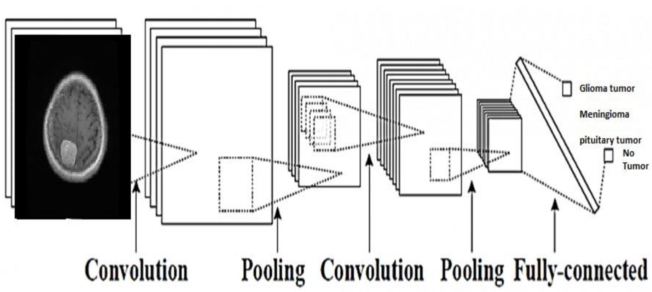
Our CNN Model consists of flatten layer and fully connected layer. In our project the pre-processed input data are trained DCNN Models. And the test data are classified by using the trained model Finally we can get the predicted Class (Brain Tumor or not) for the test image as output.

CONVOLUTIONAL NEURAL NETWORK

In deep learning, a convolutional neural network (CNN, or Conv Net) is a class of deep neural networks, most commonly applied to analyzing visual imagery.[1] They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation invariance characteristics.[2][3] They have applications in image and video recognition, recommender systems,[4] image classification, medical image analysis, natural language processing,[5] and financial time series.[6]

CNNs are regularized versions of multilayer perceptron's. Multilayer perceptron's usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The "fully-connectedness" of these networks makes them prone to overfitting data. Typical ways of regularization include adding some form of magnitude measurement of weights to the loss function. CNNs take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble more complex patterns using smaller and simpler patterns. Therefore, on the scale of connectedness and complexity, CNNs are on the lower extreme.

ARCHITECTURE OF CNN



STEPS IN CNN

Step 1: Convolution

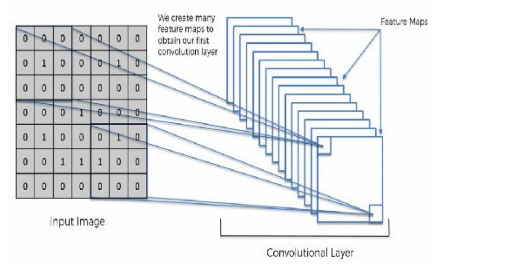
Step 2: Max pooling

Step 3: Flattening

Step 4: Fully connection

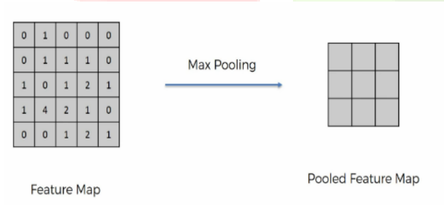
CONVOLUTION:

Convolutional layers convolve the input and pass its result to the next layer. This is similar to the response of a neuron in the visual cortex to a specific stimulus.[12] Each convolutional neuron processes data only for its receptive field. Although fully connected feedforward neural networks can be used to learn features as well as classify data, it is not practical to apply this architecture to images. A very high number of neurons would be necessary, even in a shallow (opposite of deep) architecture, due to the very large input sizes associated with images, where each pixel is a relevant variable. For instance, a fully connected layer for a (small) image of size 100 x 100 has 10,000 weights for each neuron in the second layer. The convolution operation brings a solution to this problem as it reduces the number of free parameters, allowing the network to be deeper with fewer parameters.[13] For instance, regardless of image size, tiling regions of size 5 x 5, each with the same shared weights, requires only 25 learnable parameters. By using regularized weights over fewer parameters, the vanishing gradient and exploding gradient problems seen during backpropagation in traditional neural networks are avoided.[14][15].



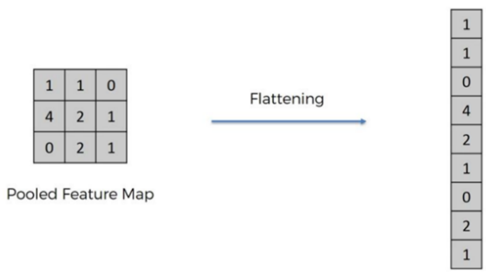
POOLING:

A **pooling** layer is another building block of a **CNN**. Its function is to progressively reduce the spatial size of the representation to reduce the number of parameters and computation in the network. **Pooling** layer operates on each feature map independently. The most common approach used in **pooling** is max **pooling**.



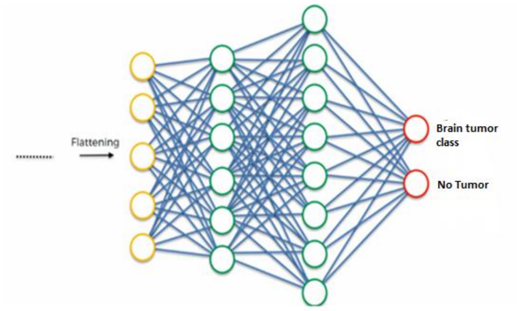
FLATTENING:

Flattening is converting the data into a 1-dimensional array for inputting it to the next layer. We **flatten** the output of the convolutional layers to create a single long feature vector. And it is connected to the final classification model, which is called a fully-connected.

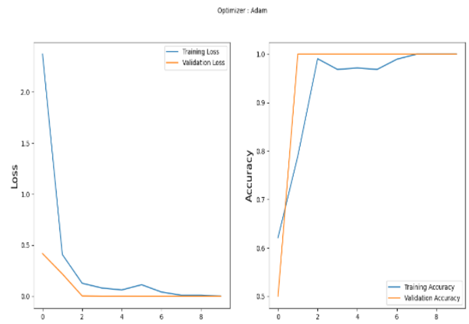


FULLY CONNECTION:

Fully connected layers connect every neuron in one layer to every neuron in another layer. It is in principle the same as the traditional perceptron neural network (MLP). The flattened matrix goes through a fully connected layer to classify the images.



LOSS AND ACCURACY GRAPH



CONCLUSION

In this project, we have proposed brain tumor detection using deep convolution neural network, which utilizes an implicit reverse attention and explicit edge-attention to improve the identification of infected regions. Our system has great potential to be applied in assessing the diagnosis of Brain Tumor, e.g., quantifying the infected regions, monitoring the disease changes, and screening processing. This proposed model is able to detect the objects with low intensity contrast between infections and normal tissues.

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