ECE 910 Report

Brain tumour detection using convolutional neural networks (CNN)

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Abstract

A brain tumour is an intracranial solid neoplasm that develops inside the brain or central spinal canal. Because the brain is such a delicate component of the human body to treat, brain tumours are inherently dangerous and life-threatening diseases. Brain tumours, on the other hand, can be malignant (cancerous) or benign (non-cancerous). The segmentation, identification, and extraction of tumours from magnetic resonance (MR) images is a time-consuming and tedious task conducted by radiologists or clinical specialists, and its accuracy is dependent on their expertise. Medical imaging is crucial in the diagnosis of brain tumours. For detection of unusual growth of tissues and blocks of blood in nervous system MR Images can be used. In this project Convolutional Neural Network is used for tumour detection. The proposed deep learning model is used on dataset obtained from Kaggle. Using deep learning techniques, this project presents an automated computer-aided approach for recognising and finding brain cancers in brain MRI scans. The performance of the proposed system is analysed in terms of validation loss, test loss, validation accuracy, test accuracy and F1 score on set of brain images. There are rigorous documents, simple guides, and high-quality open-source code available for your use. I'd like to share a basic understanding of it here to give you a head start, and then we can move on to building our model.

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Chapter 1

Introduction

Cancer is one of the deadliest diseases being very prominent in the recent times. A tumour is an abnormal growth of cells within the body which hinders proper functioning of body and makes a person ill. Brain tumour is the most dangerous among all types of cancer. The tumour can be classified as malign or benign. Malignant tumour refers to being dangerous and is risk for life while benign tumour refers to non-dangerous. A brain tumour is one of the most common causes of death in children and adults. An estimated 55,000 Canadians are living with a brain tumour. Because there are over 120 distinct forms of brain tumours, effective therapy is extremely difficult. Every year, an estimated 23.5 new instances of primary brain tumours are diagnosed per 100,000 people (using data from Alberta, British Columbia, Manitoba, Ontario) [1]. For study of brain tumour detection and segmentation, MR Images are very useful in recent years. For detection of unusual growth of tissues and blocks of blood in nervous system MRI Images can be used. The project is aimed at brain tumour detection from MRI images provided using CNN. A CNN model was built using the Keras library. The model comprises of 7 layers and are explained in this paper. The brain tumour dataset [18] used for this project is taken from Kaggle and the dataset has 243 images belonging to 2 classes (yes and no). Since the dataset is small, we performed data augmentation and normalization for reliable predictions. There was no misclassification, and significant results were obtained. The organization of the paper goes as follow. The next section has Literature survey followed by the dataset used, data pre-processing techniques employed in this model, methodology, the results obtained through this model and conclusion.

Chapter 2

Literature survey

Research is done on brain tumour and the methods been implemented for its detection and classification. The following shows the details about brain tumour and proposed models for its detection.

2.1 Brain Tumour Detection

Varalakshmi et.al. [2] proposed a methodology in which the AlexNet model is used as basic model in conjunction with the Faster R-CNN algorithm's Region Proposal Network (RPN) to classify various types of tumours. During training, the concept of transfer learning is applied. The proposed technique improves the accuracy of predicting the proper type of tumour. Kaldera et.al. [3] wrote about his proposed model in which there are fewer computations and improved accuracy. This research offers a Convolutional Neural Network (CNN) for classification and a Faster Region based Convolutional Neural Network (Faster R-CNN) for segmentation problems. The method had an accuracy of 100% in Meningioma and 87.5 percent in Glioma diagnoses, and an average confidence level of 94.6 percent in segmentation of Meningioma tumours, according to this study, which employed 218 photos as a training set. Ground truth analysis and manual analysis by a Neurologist are used to validate the segmented tumour regions.

Ali et. al. [4] in his paper, proposed a methodology to process and classify tumour images utilising Residual networks with skip connections to improve performance. The methodology also advances in reducing complexity and overfitting. Resnet is complex in nature and takes a long time to run, even though there are skip connections. Amin et. al. [5] proposed a novel method of employing CNN with batch normalisation to detect Glioma and stoke lesions, which has been tested in several databases. Choudhury et.al[6] proposed a work which involves the approach of deep neural network and incorporates a CNN based model to classify the MRI based on tumour detection. The model captures a mean accuracy score of 96.08% with f_score of 97.3%.

Vijay et. al. [7] proposed An Efficient Brain Tumour Detection Methodology Using K means Clustering Algorithm. This research offers an effective approach for extracting tumour tissues from MR images using automated brain tumour segmentation. For improved performance, segmentation is performed utilising the K-means clustering algorithm in this technique. This improves tumour borders and is much faster than many other clustering techniques. The proposed approach yields positive outcomes. Bandana Sharma et al. [8] proposed a method for brain tumour detection using pattern recognition techniques. This research presents a genetic algorithm and SVM-based categorization of brain tumours. It is argued that Gabor filters are inadequate owing to their lack of orthogonality, which results in duplicate features at different sizes or channels. While Wavelet and quadtree Transform can represent textures at the most suitable scale, by varying the spatial resolution and there is also a wide range of choices for the wavelet and quadtree function.

D. Saraswathi et. al. [9] presented An Automated Diagnosis system using Wavelet based SFTA Texture Features. The Wavelet-based SFTA Feature extraction approach (WSFTA) described in this study consists of two steps: (i) The input picture is first decomposed into different frequency sub band images using the 2-D Discrete Wavelet Transform, and (ii) texture characteristics are recovered from the decomposed Low frequency image using SFTA (Segmentation based Fractal Texture Analysis). A two-layered feed forward neural network is used to classify MRI brain pictures as normal or pathological. In terms of MSE and classification accuracy, the suggested approach outperforms GLCM and Haralick's texture feature. It also has a higher accuracy and a lower MSE of 98.0 percent and 0.585 percent, respectively. Therefore, the resulting WSFTA approach outperforms the earlier research.

2.2 CNN Architecture

Artificial Intelligence and Machine learning has become very popular and brought remarkable changes in the field of technology. Among these, Convolutional neural networks (CNN) are often used in deep learning to evaluate visual data have made significant advancements in the field of image processing, allowing for the exact execution of any classification or segmentation task, which is critical in biomedical applications. When compared to other image classification methods, CNNs require very minimal pre-processing. This implies that, in contrast to traditional methods, the network learns to improve the filters (or kernels) through automatic learning. Convolutional layers, pooling layers, ReLu layers, and fully linked layers make up a CNN. The features are extracted by using the convolutional layer from the image, such as edges, lines, and so on. It uses a sliding window matrix and convolution to extract the features. A filter, often known as a kernel, is a device that can be used to filter data. The filter does a pixel-by-pixel calculation operation with a subset of the input image pixels and the results of pixel-by-pixel multiplication are added together. The filter then moves across the entire image, performing the same operation. In CNN terminology, the result of each convolution process is now concatenated into a matrix called a feature map. Depending on the situation, there will be a few convolutional layers due to the application's complexity The essential information, such as edges and gradients, appears to be captured by the first layers. The last layer catches the intricate details of the subject image created by combining the findings of the first layers.

The convolution operation explained above is represented as shown in the equation below. Consider am image with input I of pixel size (x, y), a convolutional kernel F of size (n ,n) and output feature map S of size (i, j), the convolution can be defined as:

$$S[i,j] = (I \times F)[i,j] = \sum_{p} \sum_{q} F(p,q) \times I\ [\ i-p, j-q]$$

In addition to the convolutional layer, we also have a pooling layer which is similar to it. The pooling layer is responsible for reducing the spatial size of the convolution layer feature. Through dimensionality reduction, the computation power required to process the data is reduced. The pooling is of two types: Max pooling and Average pooling. Max Pooling returns the maximum value from the Kernel-covered region of the picture. Average Pooling, on the other hand, returns the average of all the values from the region of the picture covered by the Kernel. Max pooling is found to be suitable for the model and brought significant results, hence max polling is used. Pooling is very useful in extracting dominating characteristics that are rotational and positional invariant, hence sustaining the model's successful training process. The figure below represents a typical CNN network architecture.

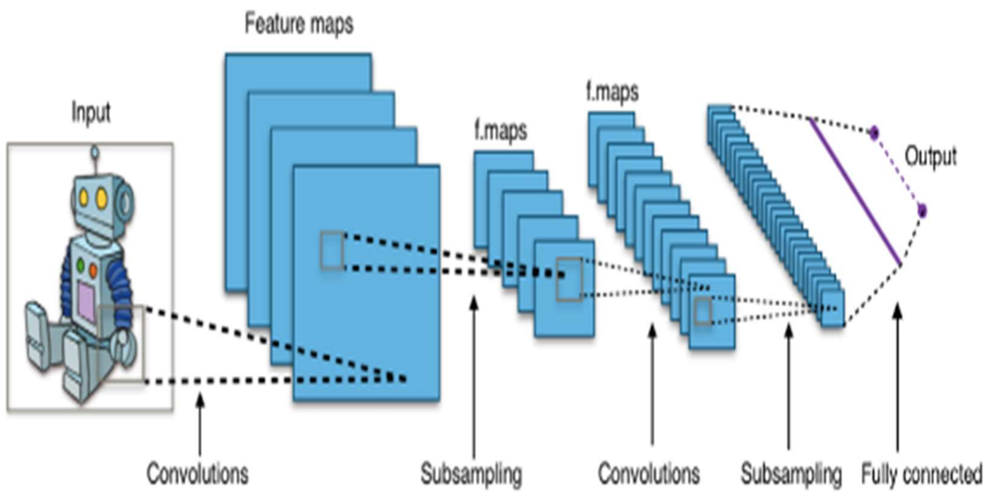


Fig 2.1: Typical CNN Network [wikipedia]

2.2.1 VGG:

VGG stands for Visual Geometry Group, and it is a multilayer deep Convolutional Neural Network (CNN) architecture. The term "deep" refers to the number of layers in VGG-16 or VGG-19, which have 16 or 19 convolutional layers respectively. The VGG architecture serves as the foundation for cutting-edge object recognition models. We used VGG 16 model in our project which proved to give out significant results.

VGG16 model was proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition" [11]. There are many advantages of using the pretrained models as they are simple to incorporate and has versatile use cases from transfer learning, prediction and feature extraction.

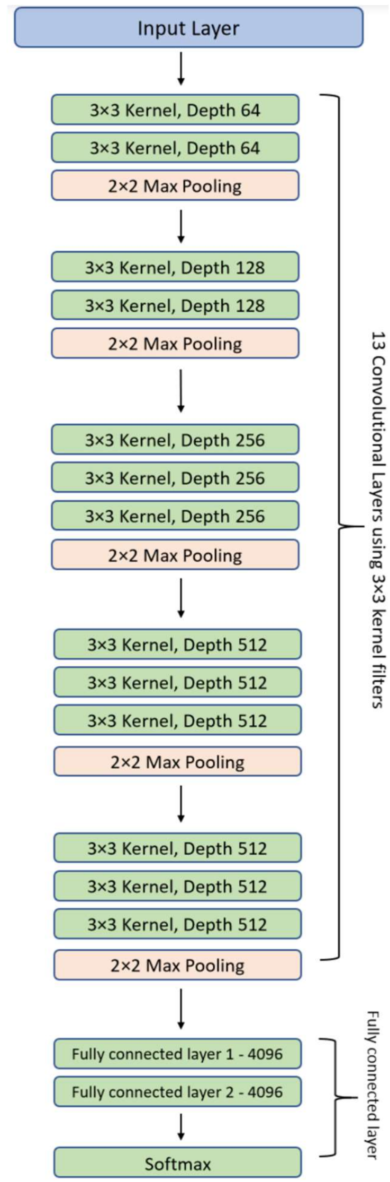


Fig 2.2: VGG 16 Architecture [12]

Srikanth et.al. [12] reviews the transfer learning with deep convolutional neural networks using VGG_16 pretrained model.

Chapter 3

Methodology and Materials

3.1 Introduction

We reviewed several techniques for brain tumour detection in chapter 2. There are many machine learning techniques, deep learning techniques and other image processing techniques used for the detection of tumour. The other techniques reviewed had certain limitations in accuracy, time taken for processing and complexity. Our model is very less complex and is easily processed compared to other models reviewed. We ran the model using traditional CNN and then followed by using VGG16 pre-trained model. The accuracy is greatly increased when VGG16 introduced in the model.

3.2 Proposed methodology

In this project the input MR images are pre-processed and are trained to get the results. Cropping is done on the images followed by data augmentation. The images are then split into test, train, and validation sets. CNN model is built using pretrained VGG16 used for training and displaying the output. Fig 2 represents the flow of the project.

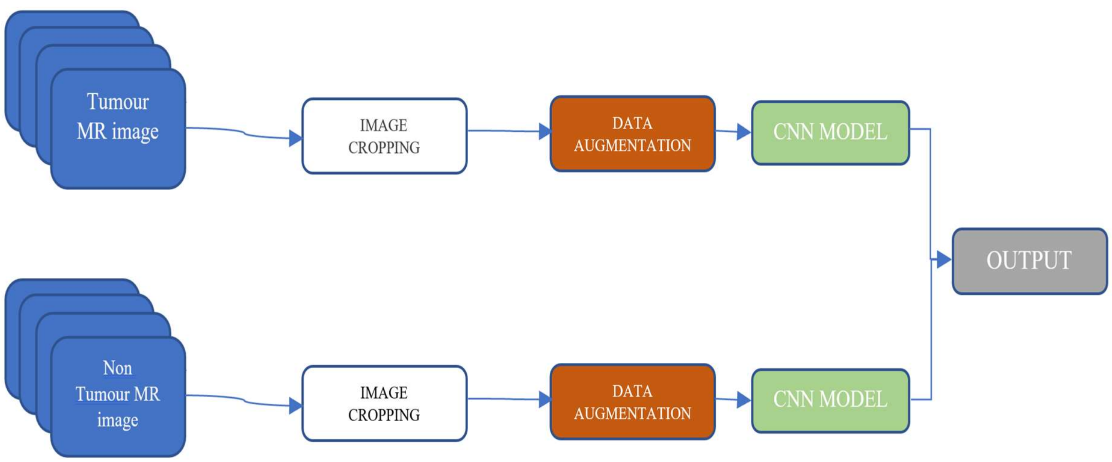
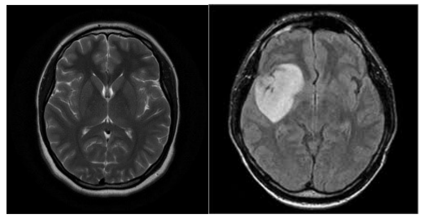


Fig 3.1: Workflow of the project

3.2.1 Image Pre-processing

The dataset used in this project has 253 Magnetic Resonant Images (MRI) of human brain of size 512x512. There are 155 images with tumour in it and 98 images without tumour. The dataset was obtained from Kaggle (and contributed by Navoneel Chakraborthy) [13].



With tumour Without tumour

Fig 3.2: Brain MR Images with and without tumour

Cropping is done to crop the brain part out of the images from the dataset of images. OpenCV is used to crop the specific part of the image which has brain. First the images are converted to grey scale using prebuilt functions. The contours in the threshold image are found and the largest one is taken as reference for cropping. Then extreme points of the image are taken, and new image is cropped out from the original image using (left, right, top, bottom) four extreme points. Since dataset used contains only few images and we require more number for samples for prediction and running the model, we perform augmentation for the images.

Data Augmentation refers to the process in which the data is converted to a larger data using slightly modified copies of already existing data or is newly created from the existing data. It acts as regularizer and helps in reliable predictions. The images in the dataset are separated and are sent into separate folders. Creation of new directories are done for the augmented images and are stored in them.

After the data augmentation, the total number of images were 1965 (1084 tumour images and 881 non-tumour images).

The dataset is split into train, test, and validation sets. 80% ((i.e., 1572) of the data is sent into training set while 10% (i.e., 197 images) is sent to validation and the remaining 10% (i.e., 196) to the testing set. In the testing set, 88 images are tumour class, and 108 images were non-tumour class.

3.3 Building model

Keras library is used to build the CNN model in this project. It uses VGG-16 pretrained model and some layers added to it. The base model VGG-16 is combined with flatten, dropout and dense layers in building the model. A dropout of 0.5 is introduced to the model to avoid overfitting problems. Also an activation function sigmoid is used in the dense layer which helps the network learn complex patterns in the data.

3.4 Summary

In this chapter the discussion is made on CNN. Building CNN model using Keras library and pretrained model VGG16, and the implementation of the project is explained.

Chapter 4

Experiments and performance evaluation

The system has been implemented on Google Collaboratory which provides installation-free GPU based training environment. VGG 16 model is taken from the Keras pretrained model and is used in building the model. The dataset is preloaded in Github and is cloned into a folder in the colab. The CNN model created has provided significant results and is compared with two other models which used the same dataset. The data from the dataset is divided into train, test, and validation sets. The performance parameters to be calculated for this analysis are:

Sensitivity = $\frac{TruePositive}{TruePositive+FalseNegative}$

Specificity = $\frac{TrueNegative}{TrueNegative+FalsePositi}$

Precision = $\frac{TruePositive}{TruePositive+FalsePositiv}$

Accuracy = $\frac{TruePositive+TrueNegativ}{TruePositive+FalsePositive+TrueNegative+FalseNegative}$

F1 score = $\frac{2*Precision*Sensitivity}{Precision+Sensitivity}$

Table 4.1 Calculating metrics for the model

Parameters	**Value**
Accuracy	97.46%
Sensitivity	97.56%
Specificity	97.40%
Precision	96.38%
F1 Score	96.97%

The metrics obtained above are calculated on the validation set. The training accuracy obtained is 100% and the testing accuracy is 97.44%. The confusion matrix calculated for the above model on the validation set is shown in figure 4.1.

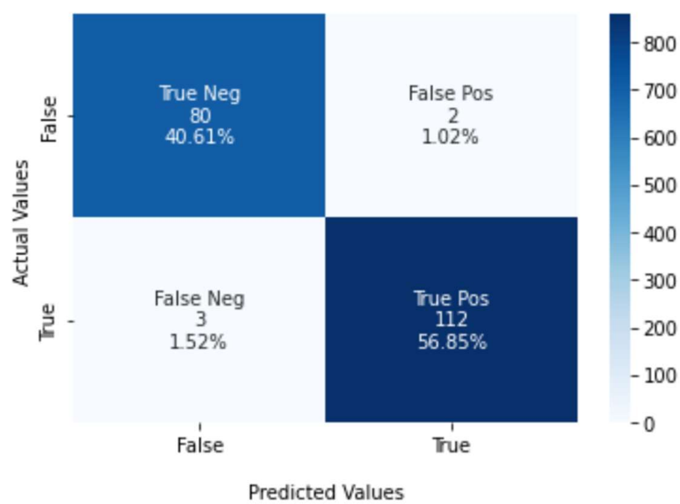


Fig 4.1: Confusion Matrix

The parameters are compared with two other models, and it is evident that the model is very less complex and gives significant results. The Mask R-CNN model was implemented in my previous work. The parameters are shown in the table below.

Table 4.2 Comparison of loss and accuracy with other models.

Parameters	**Proposed model**	**CNN VGG-19[14]**	**Resnet [15]**
Final Accuracy	97.46%	90.63%	71.88%
Final Loss	0.0812%	0.2059%	0.5463%

In the model mentioned above i.e., CNN using VGG-19 the training is done on the same dataset used for the proposed model in this paper. The accuracy obtained in this model is shown in the table 4.2.

In the case of Resnet with Faster R-CNN the training is done on the same dataset as mentioned above and the final accuracy is shown in the table above.

Chapter 5

Conclusion

We used Convolutional Neural Network to predict whether the subject has Brain Tumour or not from MRI Images. The previous work is done using Mask R-CNN and the model is very complex compared to the model implemented in this project. In this project the model was built from the scratch and can be implemented easily.

The model worked well and resulted accuracy greater than the other models under comparison. This research combined a CNN model classification challenge (predicting whether a subject has a brain tumour or not) with a computer vision problem (to automate the process of brain cropping from MRI scans).

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