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

Attention-Based CNN for Automated Brain Tumor Detection in MRI Scans

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***Abstract*— Early detection and treatment of brain tumors are crucial for effective management of brain-related diseases. With timely identification, medical interventions can be initiated promptly, potentially preventing the tumor from progressing to advanced stages. Manual detection methods are time-consuming, labor-intensive, and prone to human error, leading to delays in diagnosis and treatment. In this research, we propose a novel Convolutional Neural Network (CNN) architecture for automated brain tumor detection using Magnetic Resonance Imaging (MRI) scans. Our approach incorporates an attention-based method, enabling the model to focus on specific tumor classes during training. We curated dataset consisting of brain MRI scans, comprising of glioma tumor, meningioma tumor, pituitary tumor, and healthy brain. Statistical analysis was conducted to assess intra-class variance and determine class weights. By assigning different weights to each class, our model learned to prioritize certain classes during training. To augment the dataset, we employed a concatenation method instead of traditional data augmentation techniques. This involved concatenating the outputs of selected layers and performing max-avg pooling operations. The resulting images were subtracted to create a new set of diverse images, effectively expanding the dataset size.**

Our attention-based CNN model achieved an impressive overall accuracy of 91 percent for brain tumor detection, with consistent accuracy, precision, recall, and F1-scores across all classes.

***Keywords*—** *Convolutional Neural Network, Magnetic Resonance imaging, glioma tumor, meningioma tumor, pituitary tumor.*

1. Introduction

A brain tumour is a growth of abnormal cells in or near the brain. These cells undergo changes in their DNA, causing them to grow quickly and continue living when healthy cells would die as part of their natural life cycle. This leads to the formation of a mass or growth called a tumour. Brain tumours can develop in any part of the brain or skull, including its protective lining, the brainstem, the sinuses, and many other areas. A glioma tumour is a type of brain tumour that originates from glial cells, which are supportive cells that surround and protect nerve cells in the brain and spinal cord. Gliomas can occur in different parts of the brain and can be classified into various types based on the specific type of glial cell involved, such as astrocytoma, ependymomas, and oligodendrogliomas.

A meningioma tumour is a type of primary central nervous system (CNS) tumour that develops in the meninges, which are the layers of tissue that cover the brain and spinal cord. Meningiomas are the most common type of primary brain tumour. A pituitary tumour is an abnormal growth of cells that occurs in the pituitary gland, a small gland located at the base of the brain. The pituitary gland plays a crucial role in regulating hormone production and controlling various bodily functions. Pituitary tumour can disrupt the normal hormone balance in the body, leading to endocrine disorders and other health problems.

Convolutional neural networks typically consist of convolutional layers, pooling layers, and fully connected layers. Convolutional layers perform the convolution operation, extracting features from the input image. Pooling layers reduce the spatial dimensions of the features, reducing computational complexity and aiding in translation invariance. Fully connected layers are responsible for image classification based on the features extracted in previous layers.

Traditional methods of brain tumour detection often require manual interpretation and analysis of medical images by radiologists or cytotechnologists. Our proposed method can automate this process, reducing the need for extensive manual work and potentially minimizing human error. This automation can lead to faster and more consistent tumour detection.

In this research work, we have accomplished the following objectives:

- Incorporate an attention-based method into the CNN architecture to allow the model to focus on specific tumour classes during training.
- Conduct statistical analysis to assess intra-class variance and determine class weights, allowing the model to prioritize certain classes during training.

- Employ a concatenation method to augment the dataset, generating diverse images by performing max-avg pooling operations on the outputs of selected layers and subtracting the resulting images.
- Develop a Convolutional Neural Network (CNN) architecture for automated brain tumor detection using Magnetic Resonance Imaging (MRI) scans.
- Measure the performance of the attention-based CNN model in terms of overall accuracy, precision, recall, and F1-scores across all classes.

2. RELATED WORK

Komal Sharma et al. [1] proposes method to classify brain tumor by first extracting texture features using Gray Level Co-occurrence matrix and then classification is done using machine learning algorithm. 66 percent of images are used in training and remaining are used for testing. Multi layer perceptron performed with 98.6 percent accuracy while the naïve bayes gave 91.6 percent accuracy.

Alexander Selvikvåg Lundervold et al. [2] lists the major CNN models available and their descriptions. This research paper gives brief introduction to deep learning with pointers to core references. It provides a starting point for people interested in deep learning and want to contribute to this field in future. Overview of deep learning concepts, Image Acquisition, QSM and MR finger printing, image restoration and image synthesis is provided in this research paper.

Benjamin Billot et al. [3] proposes a CNN which segment brain MRI scans of any contrast without retraining. Synthetic data is generated and the CNN model is trained on the synthetic images, due to which domain independence is achieved. The results show that synthseg maintains a very good accuracy for all tested resolutions. Despite the considerable loss of information at LR and heavy PV effects, SynthSeg only loses 3.8 Dice points between 1mm and 7mm slice spacing on average.

B. Devkotaa et al. [4] proposes mathematical morphological reconstruction method to detect brain tumor from mri images. Image is pre-processed to remove noise and artifacts and then segmentation operation is performed to find region of interest with tumor. Image pre-processing is done using median filter and segmentation of region of interest is done by mathematical morphological reconstruction. The classification was done using SVM.

Dena Nadir George et al. [5] proposes 2 machine learning algorithms to predict brain tumor from MRI images. However, before the data is fed to these algorithms, various shape related features are extracted using sigma filtering, adaptive threshold and region detection. After feature extraction the data is fed into 2 classifiers. The first classifier is decision tree algorithm and the 2nd classifier is multi layer perceptron. The decision tree algorithm achieves accuracy of 91.1 percent while the multi layer perceptron achieves accuracy of 95.2 percent.

Emrah Irmak et al. [6] proposes 3 different CNN models for the classification of brain tumor MRI images from 3 different datasets and compared the performance of the models. Classification-1 has 13 weighted layers (1 input, 2 convolutions, 2 ReLU, 1 normalization, 2 max pooling, 2 fully connected, 1 dropout, 1 SoftMax and 1 classification layers). It classifies an image into 2 classes. The proposed CNN model for Classification-2 has 25 weighted layers (1 input, 6 convolutions, 6 ReLU, 1 normalization, 6 max pooling, 2 fully connected, 1 dropout, 1 SoftMax and 1 classification layers). It classifies a given image into 5 classes. The 3rd CNN model classifies glioma brain tumors into 3 grades as Grade II, Grade III, and Grade IV. The Proposed CNN model for classification 3 has 16 weighted layers (1 input,3 convolutions,3 Relu,1 normalization,3 max pooling, 2 fully connected, 1 dropout, 1 SoftMax and 1 classification layers.
Classification accuracy of 99.33% is achieved after 444 iterations using the proposed model for Classification-1 task. The AUC value of ROC curve is 0.9995.
Classification accuracy of 92.66% is achieved after 294 iterations using the proposed CNN model for Classification-2 task. The AUC value of ROC curve is 0.9981.
Classification accuracy of 98.14% is achieved after 342 iterations using the proposed model for Classification-3 task. The AUC value of the ROC curve is 0.9994.

Ian J. Goodfellow et al. [7] proposes a generative model which is able to generate a new set of images from available dataset. The images generated are very close to real images and overcome the simplification seen in the images generated by traditional data augmentation methods. In this research, simultaneously 2 models were trained. A generative model G captures the data distribution and a discriminative model D estimates the probability that the data comes from dataset instead of G. Both models play a form of Min-Max game where both try to perform better than other.

Muralikrishna Puttagunta et al. [8] deliver a deep learning approach for the study of X-Ray images. This research work provides the basics of principles and implementation of artificial neural networks, deep learning, medical image analysis in computer vision. This research paper provided a systematic review of the articles of classification, detection and segmentation on medical images based on deep learning approach.

Shtwai Alsubai et al. [9] proposes a hybrid deep learning model CNN-LSTM for classification of brain tumor from MRI scans. This model can handle high dimensional data. The MRI images are converted into grayscale and then thresholding is applied to convert these images into binary images. Erosion and dilation operations are performed to remove noise. CNN is used to extract features from the MRI images while LSTM is used as a classifier. Hybrid CNN-LSTM model achieved accuracy of 99.1 percent, precision of 98.8 percent and f1-score of 99 percent.

Sorayya Rezayi et al. [10] proposes 2 Deep Learning models for detecting 3 brain tumor classes from MRI brain scans. The dataset was increased using data augmentation. The first deep learning model was a 2D CNN. The second deep learning model was convolutional auto encoder neural network. Auto encoder was used for training while CNN was used for classification. Both of these models performances were compared along with several machine learning algorithms. First deep learning model 2D CNN achieved accuracy of 93.44 percent while the auto encoder achieved accuracy of 90 percent. Other machine learning algorithms were not able to achieve same level of accuracy as deep learning models.

Quoc Dang Vu et al. [11] proposes a novel approach to generate prototypical patterns that are mined from WSIs and their usages. A handcrafted framework is developed which is almost as good as the transformer model on WSI based cancer subtype classification. First the prototypical patterns are constructed then projections is done against these patterns. The AUC-ROC values for normal vs tumor improved by 1.2 percent(0.963 to 0.975).

Ziyu Li et al. [12] employs a U-Net and GAN for image synthesis. In this research work, it is shown that T1w images synthesized from diffusion data using CNN exhibit high quality. Resultant volumetric segmentation and cortical surfaces are accurate for various diffusion analyses. U-Net produces higher segmentation accuracy than GAN. Synthesized T1w images improve co registration between diffusion images with geometric distortion and T1w data. U-Net-synthesized images had higher signal-to-noise ratio (SNR) but were smoother. GAN-synthesized images were visually appealing with more realistic textures and appearance.

3. DATASET USED

The dataset used in our research is opensource and can be available online. The dataset contains MRI scans consisting of Glioma Tumor, Meningioma Tumor, Pituitary Tumor classes and 1 class having healthy brain images. All the classes have different number of images present in them which poses a class imbalance problem. The Glioma tumor class contains 826 images, Meningioma tumor class contains 822 images, Pituitary tumor class contains 827 images and healthy brain class has 395 images.

All the images are noise free due to which pre-processing was not necessary. However the number of images are less. Generally, in order for neural networks to learn, large amount of data is needed. However, we have overcome this problem present in our data as well. The images present in each class also have lot of variation among them, due to which if the model is not trained properly the chances of overfitting are also present.

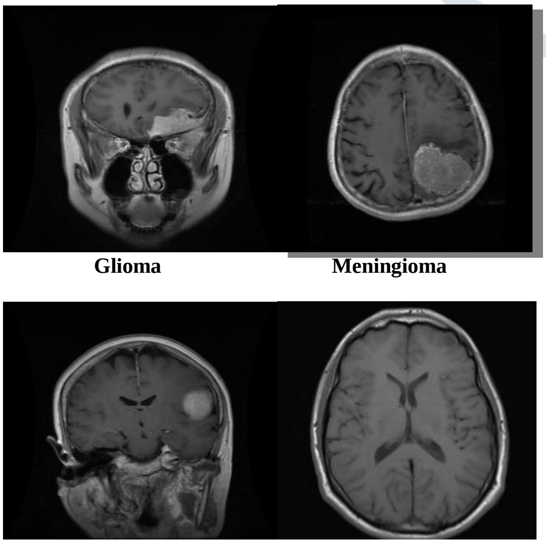


Fig 1. Samples of brain MR image

4. PROPOSED METHODOLOGY

The proposed methodology is illustrated in Fig 2. However the data collection was the first step which we have acquired opensource.

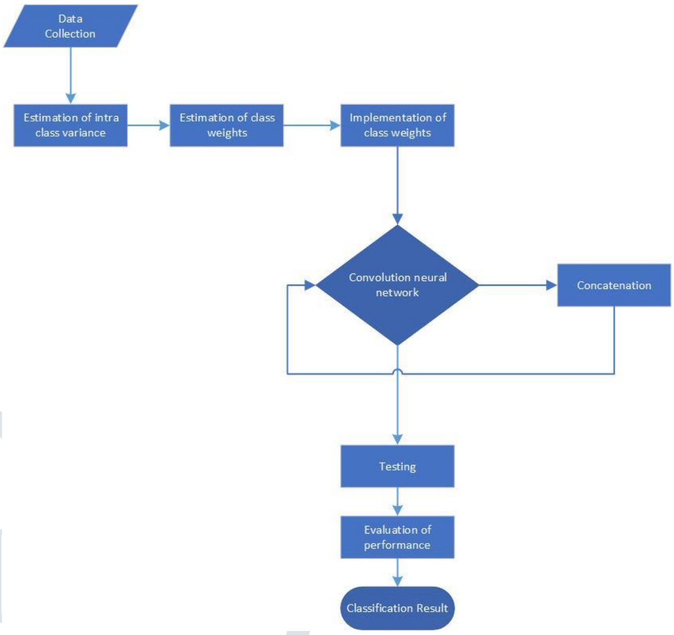


Fig 2. Flow Chart

4.1 Estimation of Intra-class variance

Based on the images present in class intra class variance is estimated for each class. This variance value provide us with the estimation of the variation in between images are present in each class. This helps us to understand the data. In our data, the classes which have high variance need more attention from our model for learning. Otherwise underfitting can occur in our model.

Estimating Attention ratio to give our model while training:

$$V(C) = (1 / N(C)) * \sum(x\_i - \mu)\hat{}2 \qquad (4.1.1)$$

Where:

N(C) is the number of images in class C.

V(C) is the intra class variance on class C.

x_i represents the individual values within class C.

μ is the mean value of class C, calculated as μ = (1 / N(C)) * ∑x_i.

4.2 Estimation of class weights

Based on the intra class variance present in each class we provide attention to our classes. By using class weights, during learning our model will give attention to the classes based on the weights provided. It makes our model attention based. Classes having high variance and a smaller number of images will be given more attention during training than class with low variance and high number of images.

$$\text{Class weight:} = [(1 / N(C)) * \sum (x\_i - \mu)\hat{}2]/N(C) \qquad (4.1.2)$$

We will normalize the class weight in the range 0-1.

4.3 Convolutional Neural Network

Develop and train a novel CNN model for tumour detection and classification.

Step1: Convolution operation: no. of filters =13, size = 3x3

Step 2: Maxpool operation: filter size 2x2

Step3: Convolution operation: no. of filters =21, size = 3x3

Step4: Maxpool operation: size = 2x2

Step5: Concatenation operation

Step6: Convolution operation: no. of filters =168, size = 3x3

Step7: Depthwise Convolution operation: no. of filters =168, size = 3x3

Step8: Depthwise Convolution operation: no. of filters = 168, Size = 3x3

Step9: Depthwise Convolution operation: no. of filters = 336, Size = 3x3

Step10: Global Average pooling layer

Step11: Output layer

4.4 Concatenation within CNN

In our Convolutional Neural Network (CNN) model, an innovative approach is implemented starting from the 3rd layer. At this stage, a set of images undergoes two distinct pooling operations: max pooling and average pooling. The resulting pooled images are then subtracted from each other, yielding a completely new set of images. This novel technique adds diversity to the training data.

Subsequently, in the 6th layer of our CNN model, these newly generated images are reintroduced through a process known as concatenation. By concatenating these images with the existing training data, the total number of training images is further increased. This augmentation technique not only expands the dataset but also introduces a fresh and distinct set of images for the training process.

The incorporation of this sophisticated approach has proven to enhance the overall performance of our CNN model. By introducing diverse and unique training images through pooling, subtraction, and concatenation, our model gains a deeper understanding of the data and is better equipped to handle complex patterns and variations. This improved performance demonstrates the effectiveness of our proposed methodology in advancing the capabilities of the CNN model.

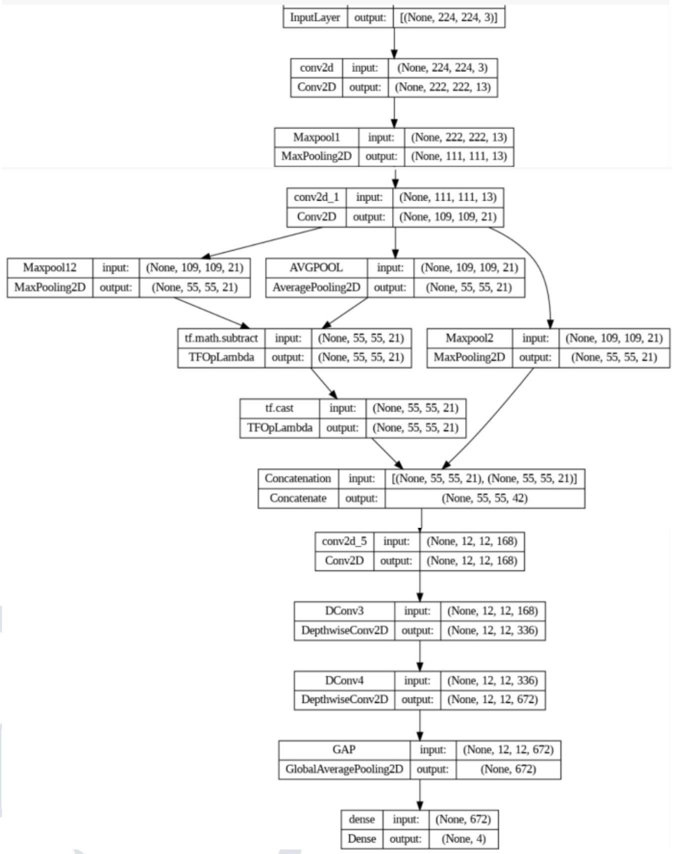


Fig 3. Model Architecture

5. Experimental Results

Below are some of the figures which shows how our model performed during and after the training period. Whether there was any difference in training and validation phase. It reflects the amount of overfitting or underfitting that occurred in the model, if any.

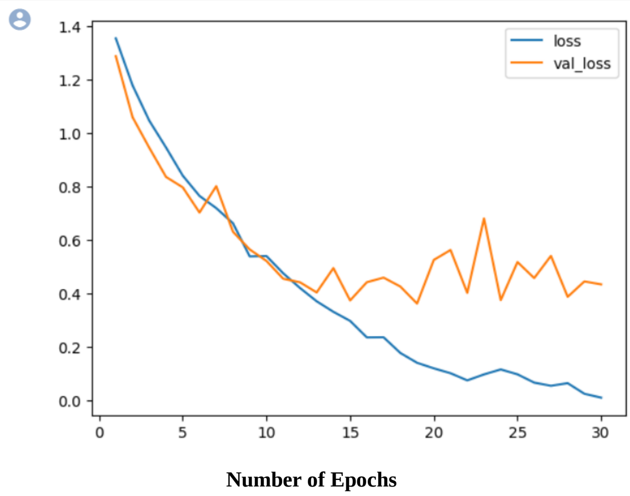
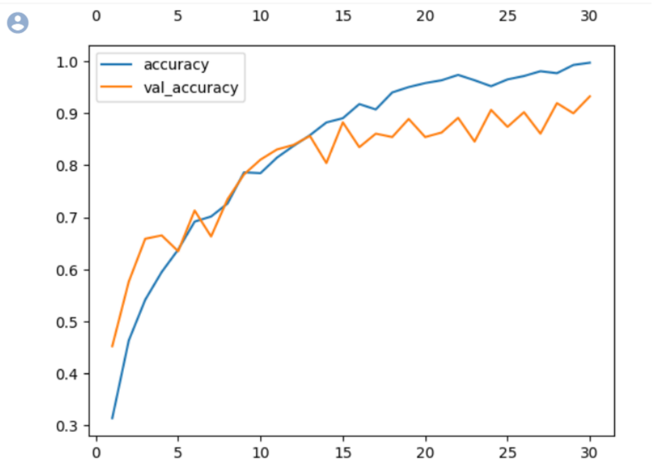
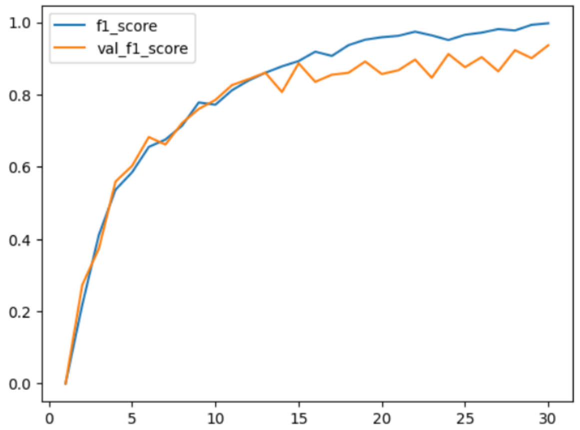


Fig 4. Training vs Validation loss



Number of Epochs

Fig 5. Training vs Validation accuracy



Number of Epochs

Fig 6. Training vs Validation F1 Score

5.1 Final Result

Tumor class	Precision	Recall	F1 Score
Glioma Tumor	0.97	0.89	0.93
Meningioma Tumor	0.82	0.91	0.86
Pituitary Tumor	0.90	0.91	0.91
Healthy images	0.95	0.92	0.93
Overall	0.91	0.91	0.91

Table 1. Performance of proposed model in each class

	precision	recall	f1-score	support
0	0.97	0.89	0.93	165
1	0.82	0.91	0.86	165
2	0.90	0.91	0.91	79
3	0.95	0.92	0.93	165
accuracy			0.91	574
macro avg	0.91	0.91	0.91	574
weighted avg	0.91	0.91	0.91	574

Fig 7. Classification report

As we can see that our model has achieved an overall accuracy of 91 percent. The dataset used in our research work contains high class imbalances, while some classes have very small number of images, other have good number of images.

Despite different number of images present in each class our model is able to perform with same accuracy, precision, recall and f1 score for all the classes overcoming the class imbalance problem.

As seen in figure 6, the f1 score while training and validation phase does not have big difference which shows that the training performance of our model is similar to the performance in validation phase. It reflects that our model did not undergo overfitting and is able to learn in a well-suited manner.

6. Conclusion

Detecting brain tumour manually is a time consuming process. Automating it can save radiologist’s time and share their workload. In our thesis, we built an Attention based novel brain tumour detection algorithm which can help radiologist to identify this disease. For this purpose, we first did statistical analysis, in which we calculated the intra class variance present in each class. By using this intra class variance and total number of images in each class we were able to formulate a mathematical formula to estimate class weights.

Using the class weights we will be proving certain degree of attention to each class. Classes in which the classification is difficult will be provided more attention. Also, to encounter the less number of images in our dataset, we used a concatenation method in which using max-avg pooling operations we were able to generate a new set of images. We used the concatenation method in our novel CNN architecture. We then trained and tested our model.

The results demonstrate that our attention-based CNN model can effectively detect brain tumours with high accuracy rates. We got overall accuracy of 91 percent. All classes has exactly the same accuracy, precision, recall and f1-score which is all 91 percent. It conclude that our model maintain stability in detecting all different tumour classes. It is not that on one class it performs really well and does not perform in another type of tumour class. In various different types of tumour it can detect while maintaining the same consistency and accuracy.

7. FUTURE WORK

We can do image segmentation in our MRI images and only use the region of interest for classification. It will decrease the model complexity drastically and our model does not have to use its resources in learning from regions which are not responsible for classification.

We can extract textures from our MRI images and feed them as an additional feature to our classification algorithm. It may improve the performance of our model.

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