Auto-Detection of Brain Tumour From MR Images Using Deep Learning

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Agenda

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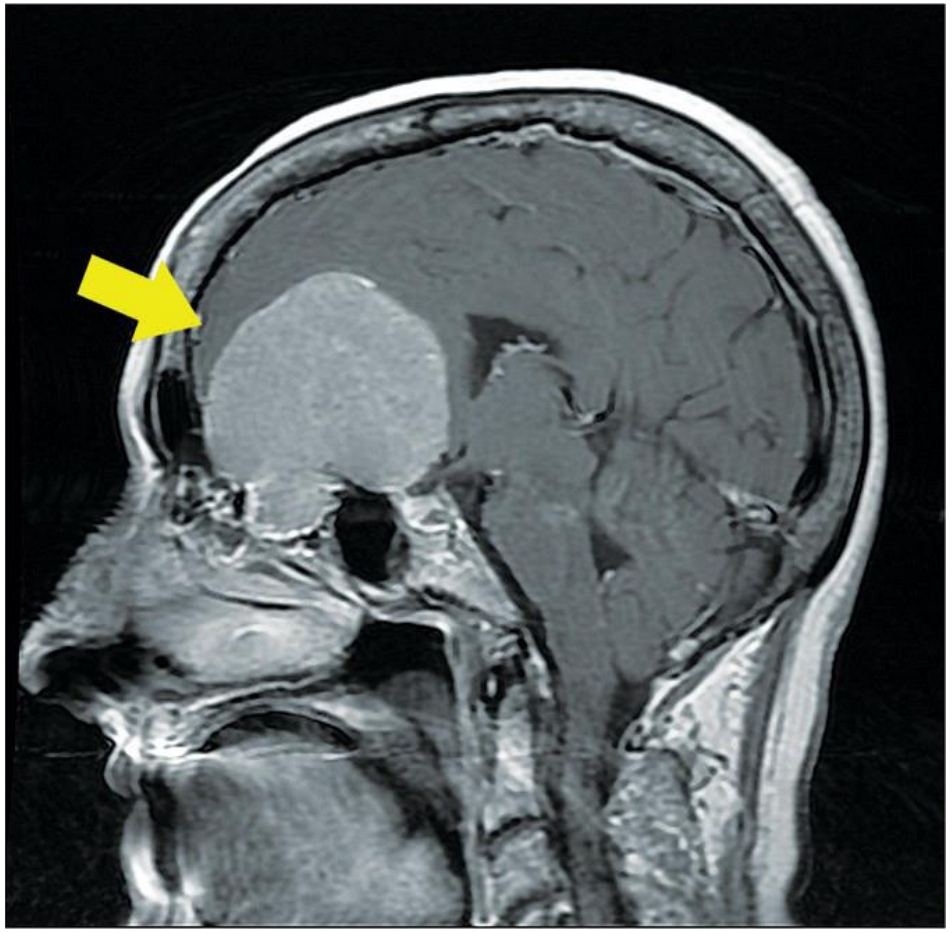
What Is Brain Tumor ?

A tumor can be defined as any mass caused by abnormal or uncontrolled growth of cells. This mass of tumor grows within the skull, due to which normal brain activity is hampered.

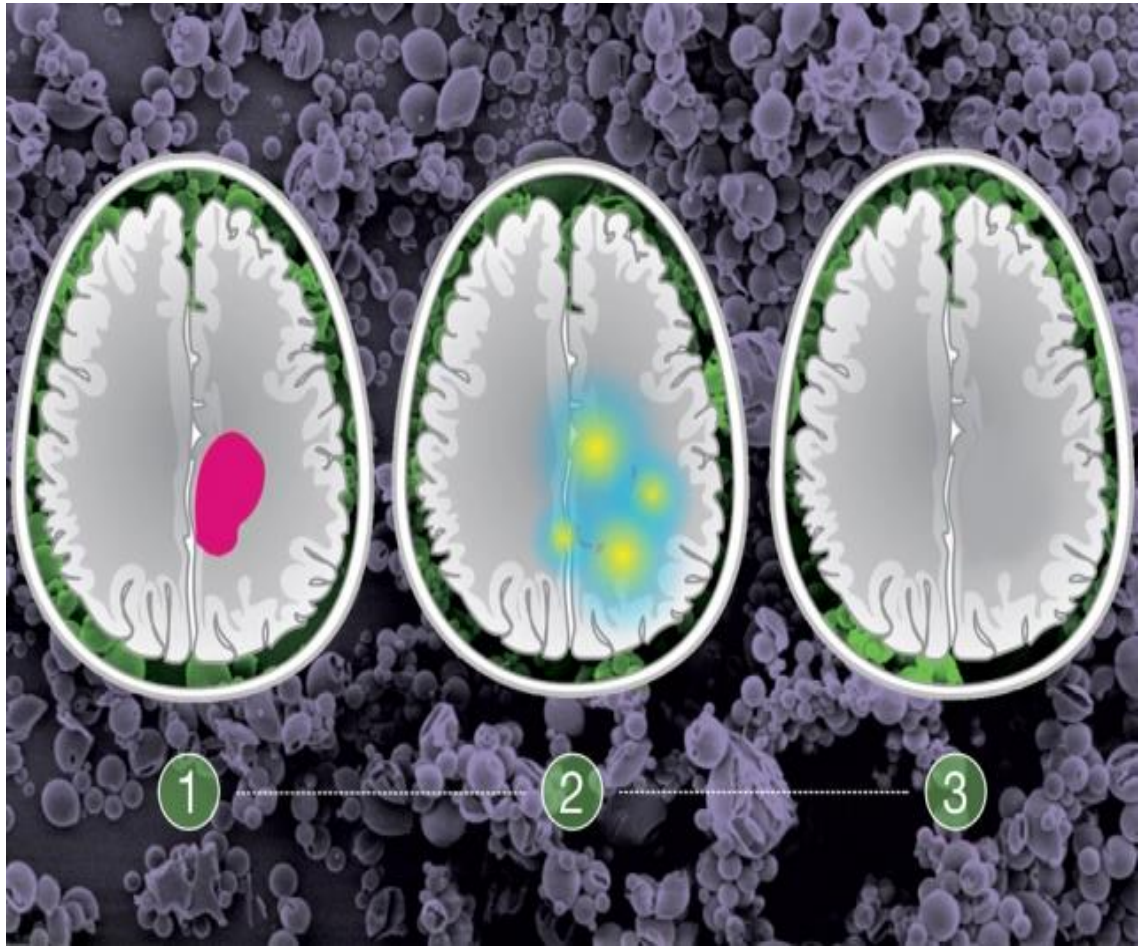
Which if not detected in earlier stage, can take away the person's life. Hence, it is very important to detect the brain tumor as early as possible.



Business Case

Brain tumor is one of the vital organs in the human body, which consists of billions of cells. The abnormal group of cell is formed from the uncontrolled division of cells, which is also called as tumor. Brain tumor are divided into two types such low grade (grade1 and grade2) and high grade (grade3 and grade4) tumor.

- Low grade brain tumor is called as benign.
- High grade tumor is also called as malignant.
- Benign tumor is not cancerous tumor.
- Malignant tumor is a cancerous tumor. So it spreads rapidly . It leads to immediate death.



Problem Statement

- For patients with brain tumor, physical symptoms vary from patient to patient
- Some patients don’t even show general symptoms
- MRI scans of patients are more reliable than physical symptoms
- MRI scans sometimes involve multiple noise types that can result in incorrect performance.

Objective

1. To study and identify the symptoms of brain tumor. Explore new possibilities for brain tumor segmentation algorithm

2. To analyze the feasibility of brain tumor. Make system enable to differentiate between tumor and non-tumor images

3. To design and develop the classification model. Comparative study between different algorithms at each stage and finally uses the algorithm which one is best

4. To evaluate the performance for CNN. Calculate area and volume of tumor

Data Gathering & Understanding

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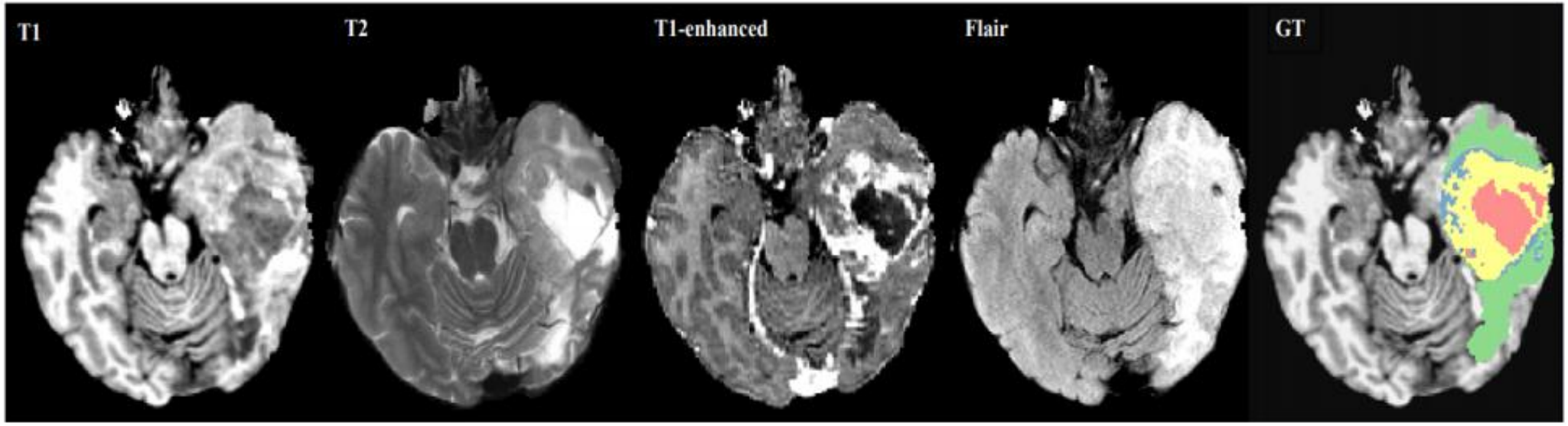
- Dataset used is BRATS – 2018 dataset
- Dataset consists of 4 modalities(different types of scans) namely T1, T1C, T2 and T2-FLAIR
- For each patient and each modality, there is a 3D image of brain
- Here in this paper the focus is on concatenating the 4 modalities as 4 channels *slice-wise*
- The slices in 4 modalities and ground truth labels are as shown below.

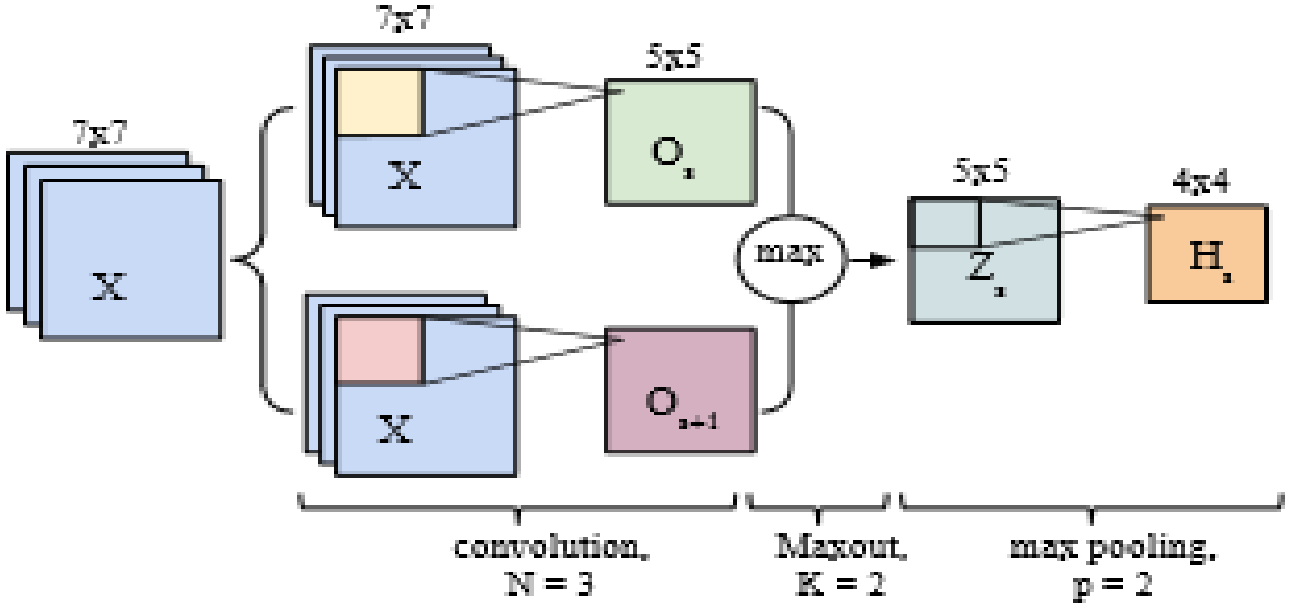


Data Preparation

- The 5 labels for ground truth are:
  - 1 : For necrosis
  - 2 : For edema
  - 3 : For non-enhancing tumor
  - 4 : For enhancing tumor
  - 5 : For everything else

Modelling

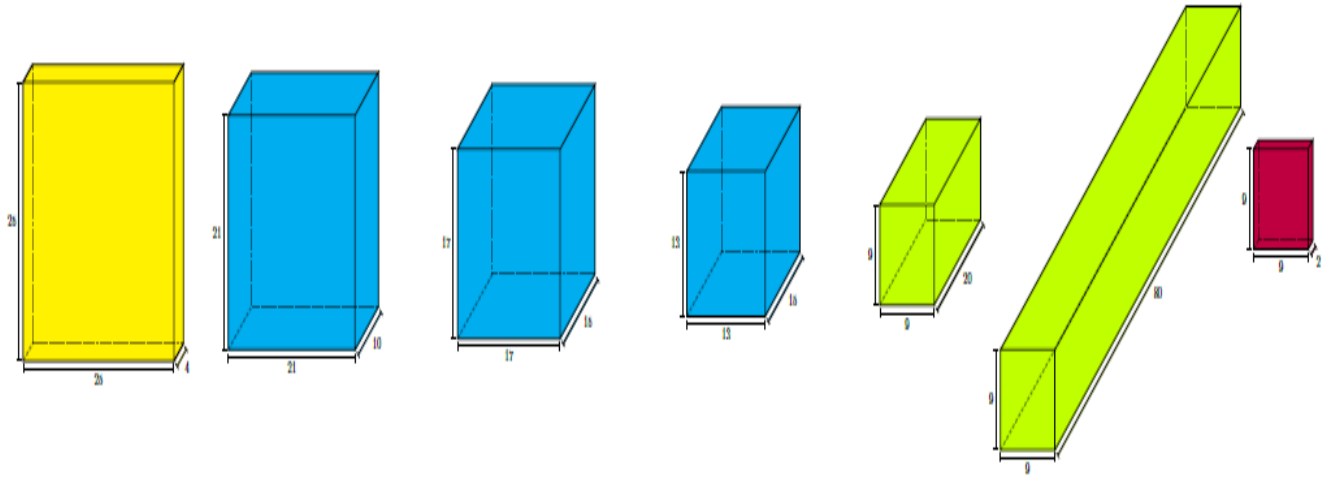
- Convolutional neural network model
- Takes a (33 x 33 x 4) patch from slice, produces one-hot encoding for 5 labels
- Layers used : Convolutional layers, max-pooling, max-out, Dropout(implemented in paper)



Modelling contd…

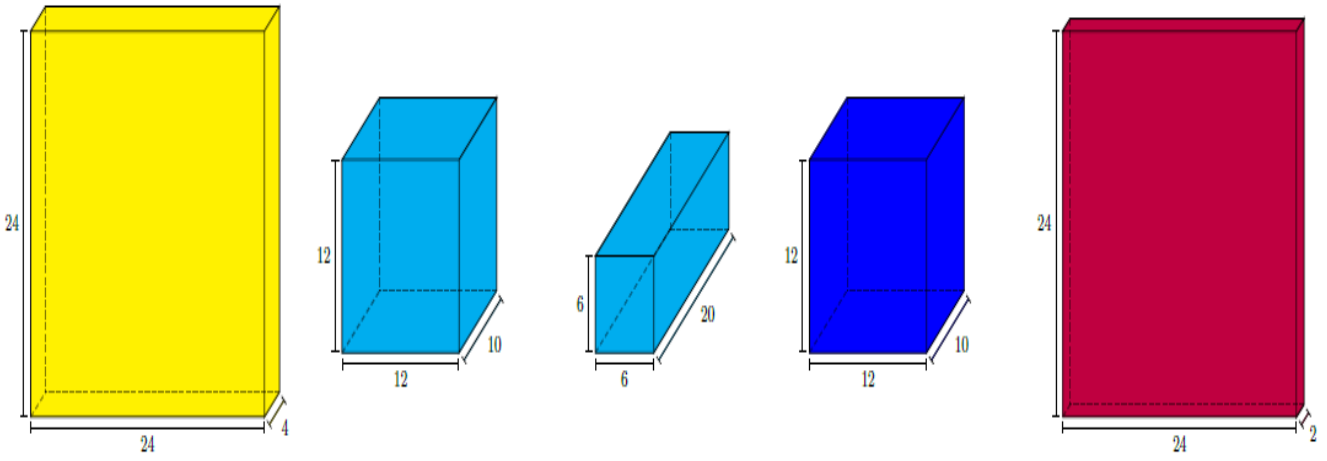
Baseline Convolutional Network (BCN)

- The Base Convolution Network (BCN) model operates by calculating voxel probabilities.
- The data is 253 x 4 volumes (single slice reflected, slice depth channels). 3D layers of convolution (cyan), accompanied by activation of ReLU.
- Completely linked layers (green) used as 13-kernel convolutions; ReLU and drop-out obey first line. History and foreground ratings (red)



Fully Convolutional Network (FCN)

- The model uses L2 regularisation and is conditioned by optimisation with Adam. Softmax cross-entropy loss.
- 3D convolution layers (cyan) with a ReLU induction, decomposition and max-pooling of two x 2 layers.
- Three-dimensional (blue) layers followed by reLU and drop-out. History and foreground scores (red) for the whole patch.



Modelling contd…

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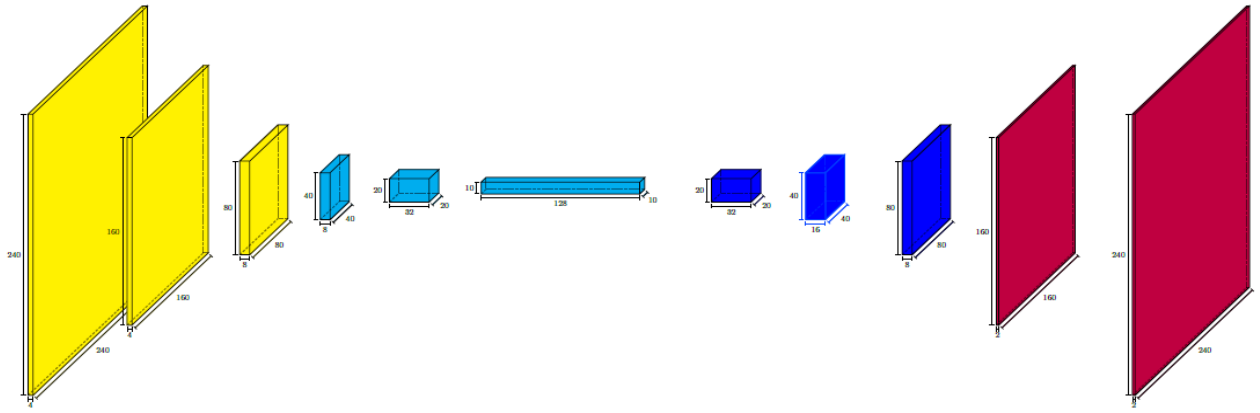
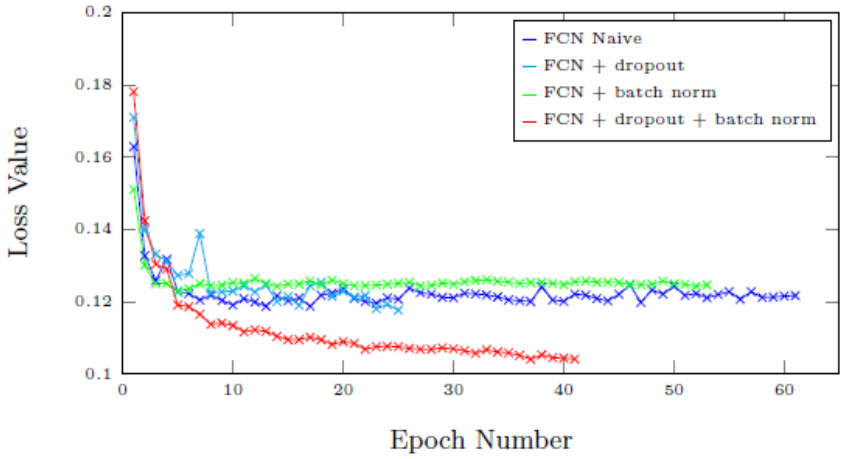
Full-image Fully Convolutional Network (FIFCN)



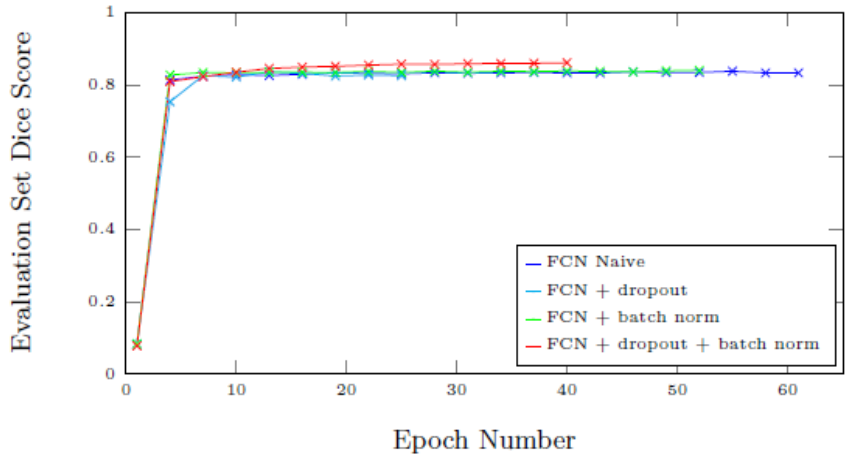
- The architecture was VGG16 but it has used the network
- of 11 layers of CNN.
- To minimise the number of parameters, first the number
- of layers are reduced to just 5 coalescing layers, from
- 8 coalescing and 3 fully connected layers.
- Second, a ~4x less filters for any film is used. It hold the ReLU activation mechanism and 2x2 max pooling for each convolutionary sheet. In order to mitigate the bias against the background class, the input volume from 240X240x155 until 160x160x144 and mitigate the sampling through 2x2 max pooling has reduced.
- The image moves through the layers of convolution and disintegration. The output of the network is 160 x 160 x 144, with estimates in tumour and history. This volume is then filled to generate the final display volume with historical pixels.
- The softmax cross-entropy loss and the loss of the dice score is now evaluated for the loss function. For regulating the L2 and train, Adam optimization is available.

Interpretation

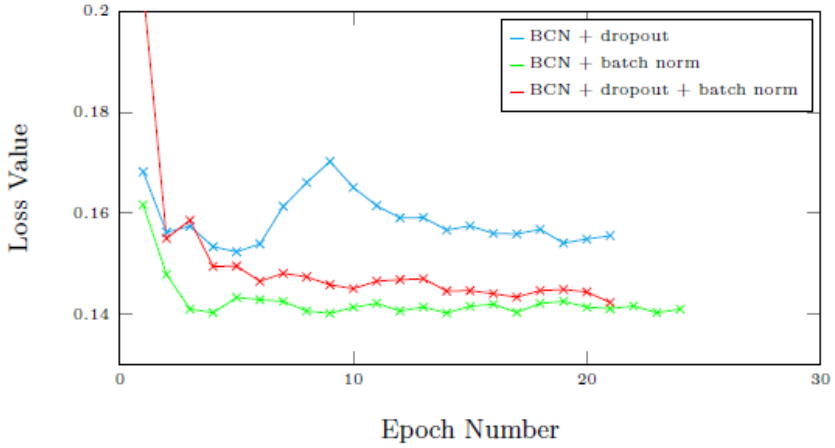
- The inclusion of dropouts and batch normalisation layers typically substantially increases the model dice performance.
- There are outstanding loses and dice ratings shown.
- It is noted that the regular and drop-out models have a comparatively lower final failure rate, but with dropout and batch standardisation the mean dice rate is significantly improved on the other models.



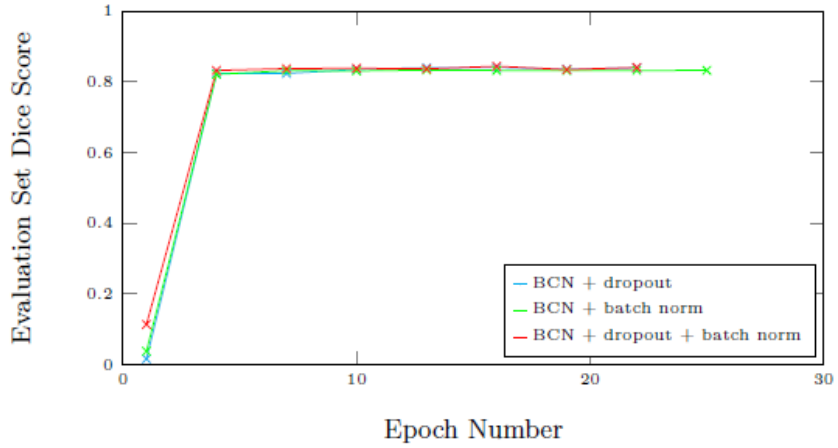
(a) FCN Loss curves



(b) FCN Dice score curves



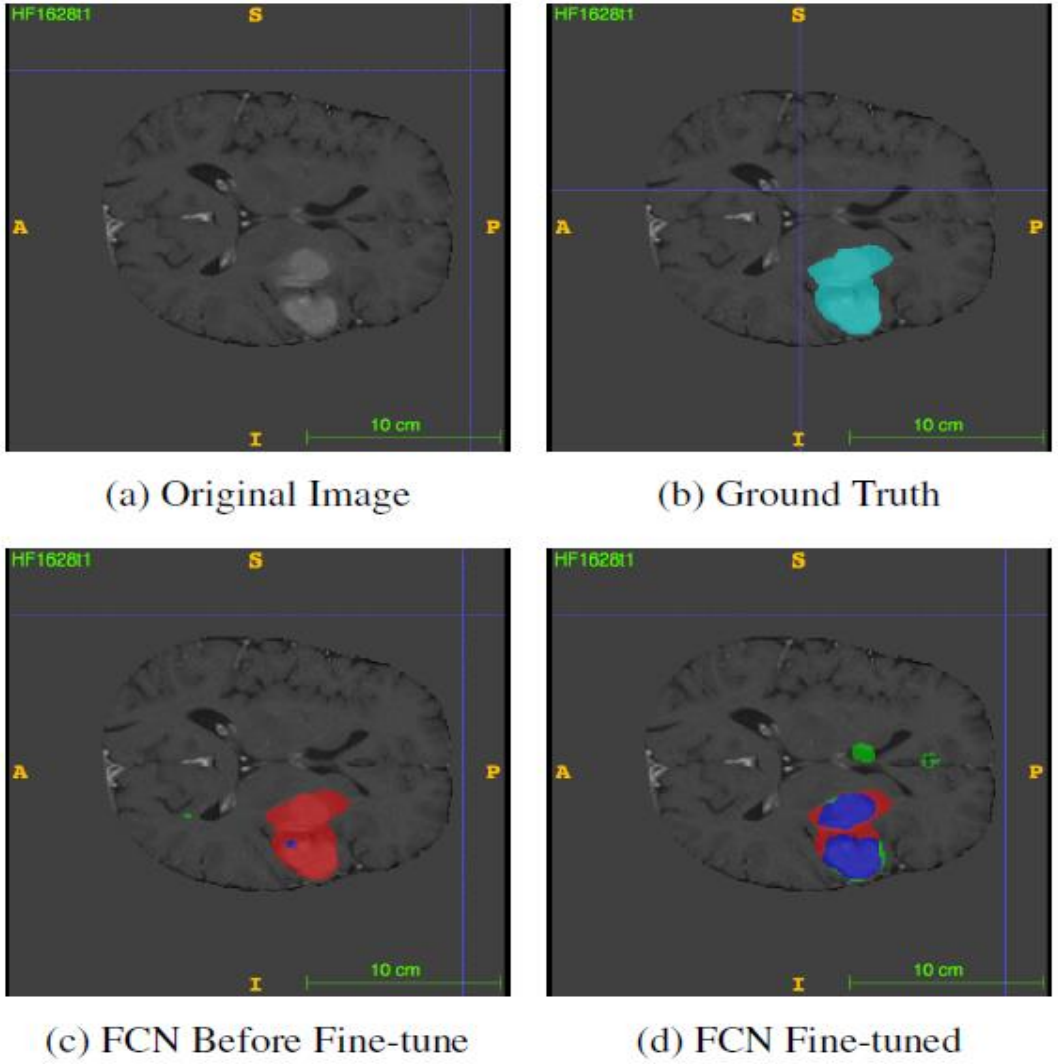
(c) BCN Loss curves



(d) BCN Dice score curves

Interpretation Contd..

- The findings reveal that the consistency of the segmentation in the validation collection is quite incompatible.
- For both models, the high and very low segmentation efficiency is observed.
- In every bin around the histogram, the fine-tuned FCN model includes samples.
- This shows that transmitting learning is not always accurate, but highly dependent upon image quality and resolution, although it can be encouraging for applications into glioma segmentation.



(a) Original Image (b) Ground Truth

(c) FCN Before Fine-tune (d) FCN Fine-tuned

Interpretation Contd..

FCN model segmented image is shown as proof. Fine-tuning the model greatly increases the segmentation efficiency, as seen in the below table.

While using the finetuning model, the number of unspecified voxels (red) is increased dramatically. The segmentation efficiency of the BraTS dataset is now higher.

Model	Method	Average Dice Score (%)
BCN	Pre-trained	80.8
BCN	Re-trained	89.2
BCN	Fine-tuned	**97.9**
FCN	Pre-trained	78.2
FCN	Re-trained	90.7
FCN	Fine-tuned	**92.2**

Conclusion

- The fine tuned FCN model has been achieving the best efficiency. It has increased the calculation in all tumour fields.
- A separation and detection mechanism focused on profound convolutionary neural networks has been introduced in this article.
- The architecture would be tailored to use during a brain procedure, to identify and to find the tumour correctly, among the other changes.
- In real-time and in real-world environments, the identification of tumours in storage space should be carried out and therefore the network should also be modified to a 3D device.
- It may be possible to detect in real time by keeping the network architecture simple.
- In future, the built neural network and enhanced network output in other medical images are to be investigated.

תודה
Dankie
Gracias
Спасибо
شكراً
Merci
Takk
Köszönjük
Terima kasih
Grazie
Dziękujemy
Dėkojame
Ďakujeme
Vielen Dank
Paldies
Kiitos
Täname teid
谢谢
Thank You
Tak
感謝您
Obrigado
Teşekkür Ederiz
감사합니다
Σας Ευχαριστούμ
ขอบคุณ
Bedankt
Děkujeme vám
ありがとうございます
Tack