BRAIN TUMOUR DETECTION USING MASK R-CNN

Biomedical Image Analysis

ECE 740 B1 – Project Report

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ABSTRACT:

A brain tumour is an unregulated development of tissues in the human brain that, when cancerous, can be fatal. There are several strategies for preventing the spread of cancer. The project's aim is to use image segmentation for brain tumour MRI (Magnetic Resonance Imaging) and detect the tumour in the X-ray image.

Artificial intelligence (AI) algorithms, particularly Deep Learning, have made significant progress in image-recognition tasks. Convolutional neural networks (CNN) and variational autoencoders, for example, have seen several applications in the medical image processing field, propelling it along at a rapid rate.[1]

In this project we employed a Mask R-CNN model which is capable of detecting tumours from MRI scans of the brain images**.** In terms of instance segmentation, Mask R-CNN has become the latest state of the art. 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.

INTRODUCTION:

One of the deadliest diseases occurring these days is cancer. Cancer is one of the most dreadful diseases which is often expected to be fatal. Tumour of the brain is the most dangerous among all cancer types. Based on its severity, brain tumours can be classified as malignant and benign. Malignant refers to being dangerous and its risk for life while benign refers to non-dangerous tumour.

According to statistics from 2012 to 2014, 63 percent of Canadians living with cancer are predicted to live for 5 years or more after diagnosis. This is an increase from 55% in the early 1990s. In the 1940s, the rate of survival was about 25%.[2]

Approximately 1 in 4 Canadians is expected to die from cancer (Figure 2.1). • The probability of dying from cancer is slightly higher for males (26%) than females (23%).[3]

Fig: Lifetime probability of dying from cancer, Canada in 2015.

The task of determining the position of a brain tumour is the first step in medical treatment. Conformal radiotherapy irradiates and kills tumour cells with high accuracy while causing little harm to nearby healthy tissues. Typically, a medical doctor knows the GTV and draws the boundary lines on machine tomography slices by hand (CT-SCAN). The CT-SCAN protocol has an effect on the irradiation preparation goal volume (PTV), whether it is determined by the same medical doctor or by the automated supporting device. The primary goal of this research is to create a computer device capable of detecting the appearance of a tumour in digital images of the brain and precisely defining its boundary line.

MRIs provide more accurate images than CT scans (see below) and are the preferred method for detecting a brain tumour. MRIs of the brain, spinal cord, or both can be performed, based on the type of tumour detected and the probability that it may spread to the CNS. There are various forms of MRI.[4]

ADVANTAGES:

- Image processing is fast.
- Quick identification of tumours is possible.
- The model can detect the presence of tumours in MRI images of the brain.
- It is highly reliable in real time operations.
- Accurate results can be found using this model.

MOTIVATION:

The aim is to create applications with improved segmentation capabilities for use in medical imaging to identify diseases such as brain tumours. Picture segmentation has been recognised as the primary issue in medical image processing, and it continues to be a common and difficult field of study. Image segmentation is rapidly being used to interpret medical imaging datasets in many clinical and academic applications, which prompted us to provide a snapshot of the constantly evolving field of medical image segmentation.

CT (Computed Tomography), MRI (Magnetic Resonance Imaging), PET (Positron Emission Tomography), and other imaging techniques produce a vast volume of image data. With advanced technologies, not only does the scale and resolution of photographs increase, but so does the number of measurements. In the future, we would like to see algorithms that can identify cancers, lesions, and tumours instantly and highlight their positions in a huge pile of photographs.

The motivation of this work is to develop a solution to detect and locate brain tumours of a patient in a very fast way unlike the traditional way which consumes a lot of time for doctors to do it and make it easier for patients.

LITERATURE SURVEY:

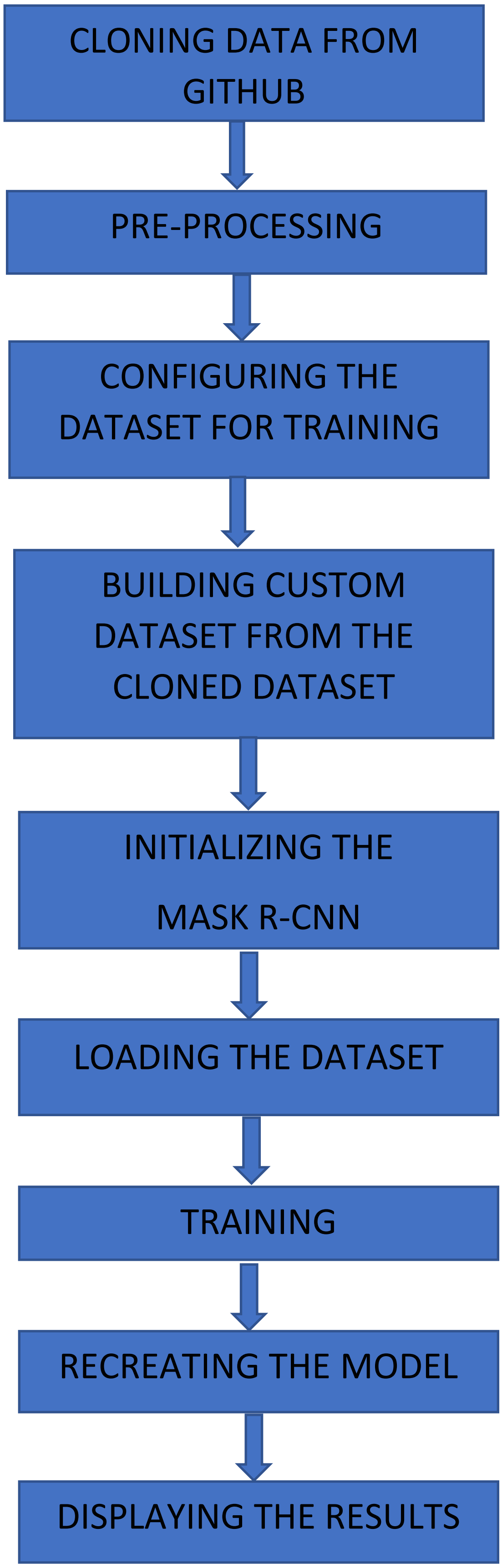
Magnetic Resonance Imaging (MRI) is a recent development in biomedical image processing that allows for the easy detection and localization of brain tumours. We intend to categorise brain scans into eight (8) distinct groups, with seven (7) representing various tumour forms and one indicating normal brain. Using the Leave 2-Out cross-validation method, the suggested classification strategy is validated. - **Muhammad Nasir, Asim Baig and Aasia Khanum.**

The magnetic resonance imaging (MRI) brain imaging technique is commonly used to image the anatomy and function of the brain. Tumour identification on MRI images necessitates many procedures such as image pre-processing, attribute extraction, image enhancement, and classification. The final classification method determines whether an individual is diseased. The benefits of segmentation algorithms are discussed. **-D. SELVARAJ, R. DHANASEKARAN.**

Because of the non-invasive imaging and strong soft tissue contrast of Magnetic Resonance Imaging (MRI) images, MRI-based brain tumour segmentation studies have gained increasing interest in recent years. With nearly two decades of growth, ground-breaking methods using computer-aided strategies for segmenting brain tumours are becoming more mature and closer to routine clinical applications. **-Jin Liu, Min Li, Jianxin Wang, Fangxiang Wu, Tianming Liu, and Yi Pan.**

Despite extensive analysis, segmentation remains a difficult problem due to the variety of image content, cluttered artefacts, occlusion, image noise, non-uniform object texture, and other variables. This paper provides an effective image segmentation method based on the K-means clustering methodology combined with the Fuzzy C-means algorithm. **-Eman Abdel-Maksoud, Mohammed Elmogy, Rashid Al-Awadi.**

METHODOLOGY:



MASK R-CNN:

Object identification is a computer vision task that involves determining the identity, position, and type of one or more objects in an image. It is a difficult issue that necessitates the development of methods for object identification, object localization, and object classification. Deep learning approaches have recently obtained cutting-edge performance for object recognition, such as on common benchmark datasets and in computer vision competitions.[5]

Mask R-CNN is used to perform instance segmentation where it involves identifying each object instance for every known object within an image. Object identification of all objects in an image is needed for instance segmentation. The aim here is to distinguish individual objects and localise each object instance by segmenting each instance using a bounding box.

Mask R-CNN is an extension of Faster R-CNN. In Faster R-CNN, for each candidate object it has a class label and a bounding-box offset. Faster R-CNN is not intended for pixel-to-pixel synchronisation of network inputs and outputs. Mask R-CNN has an additional division for predicting segmentation masks pixel-by-pixel on each Region of Interest (RoI).

Mask R-CNN Working:

Mask R-CNN model is divided into two parts

- **Region proposal network (RPN) to propose candidate object bounding boxes.**
- **Binary mask classifier to generate masks for every class.**

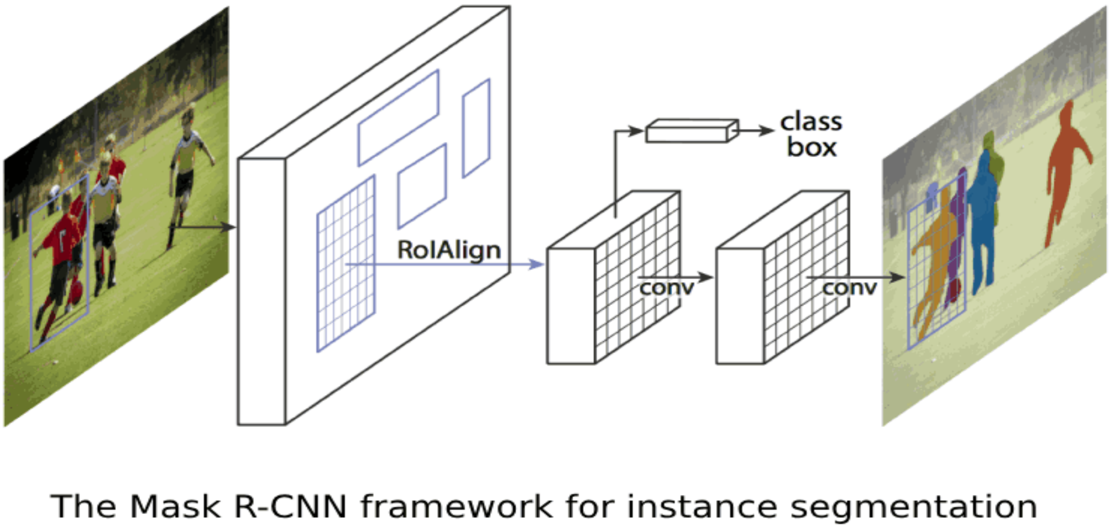


Fig1: MASK R-CNN FRAMEWORK [6]

<u>DATASET</u> [7]:

The Dataset used in this project is taken from GitHub. It consists of Images of size 512x512 with and without tumour. The images are MRI scan X-Ray images. These images are used for training and testing in the project.

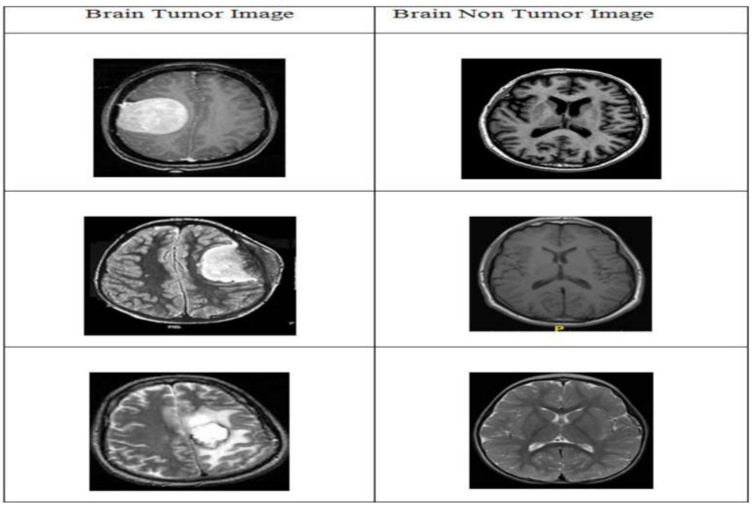


Fig2: Images with and without brain tumour

IMPLEMENTATION:

The starting point of this project is cloning the dataset from GitHub. Two datasets among which one is the MRI scan images data set by **Ruslan** [7] and the other is the Mask R-CNN repository by **Matterport**.[8]. The next step to be done is creating a directory structure of the input image data. We create the directories to save logs and trained models and the directories for the image data.

We then need to configure properties such as the number of GPUs to use as well as the number of images per GPU, the number of groups (we will usually apply +1 for the background), and so on. Count of training steps per epoch, Level of learning, Detection of skips with 85% trust.

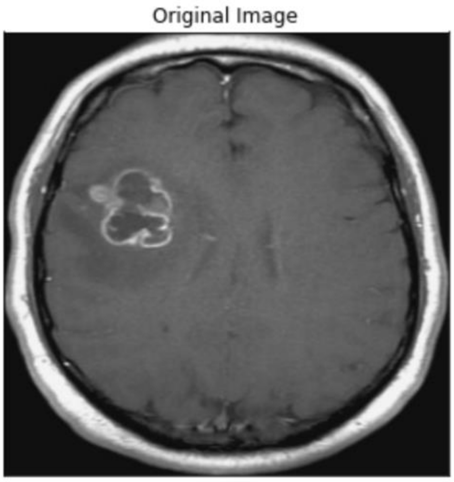
The Dataset class provides a standard interface for working with any dataset. We can generate new datasets for brain images to practise without changing the model's coding. The Dataset type also allows for the loading of several data sets at the same time. This is very useful when you try to detect several artefacts that are not all present in the same data set.

Then we load the pre-trained weights for the Mask R-CNN from the COCO data collection, minus the last few layers, and use the Config instance to initialise the Mask R-CNN model for training. We don't need to practise for too long because we're using a very limited dataset and starting from COCO learned weights. Also, there is no need to train all layers; only the heads should be trained. We trained the model for 25 epochs with the Learning rate as 0.001.

We then recreate the model in interference mode and then display the results. The output images are displayed as the comparison with images showing with and without tumour.

<u>RESULTS</u>:

1.Mask R-CNN applied to the validation dataset.



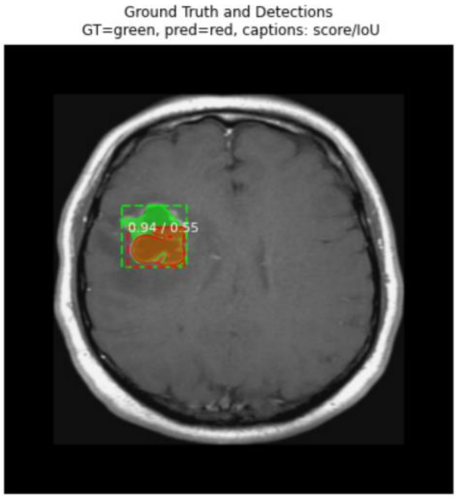
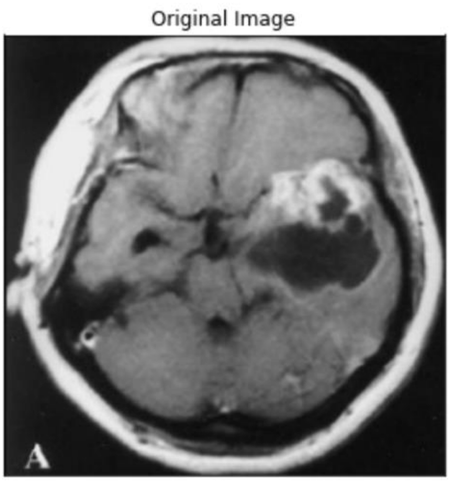


Fig: Original Image

Fig: Tumour Detected Image



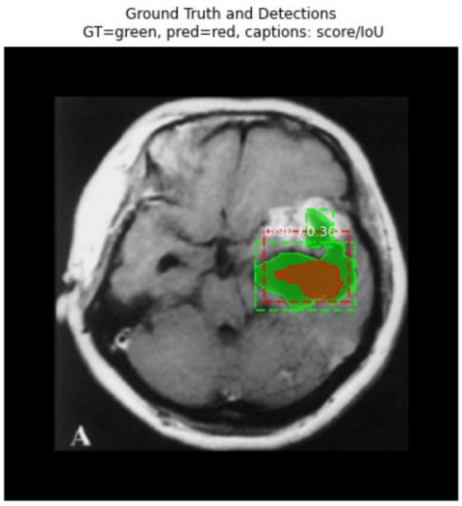
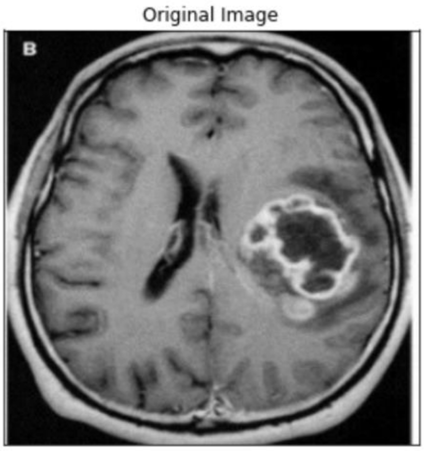


Fig: Original Image

Fig: Tumour Detected Image

2. Mask R-CNN applied on the test dataset.



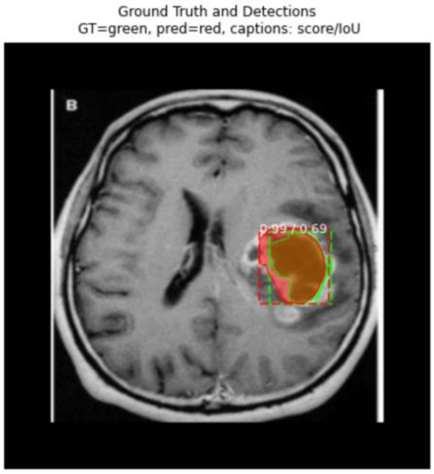
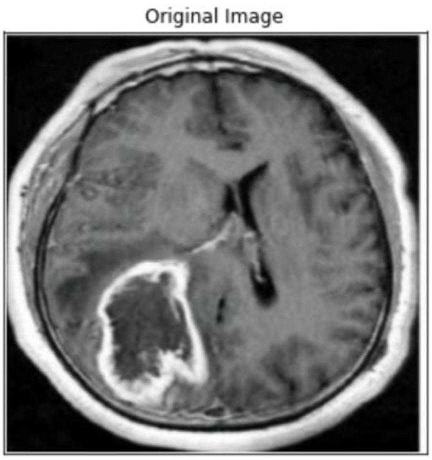


Fig: Original Image

Fig: Tumour detected Image



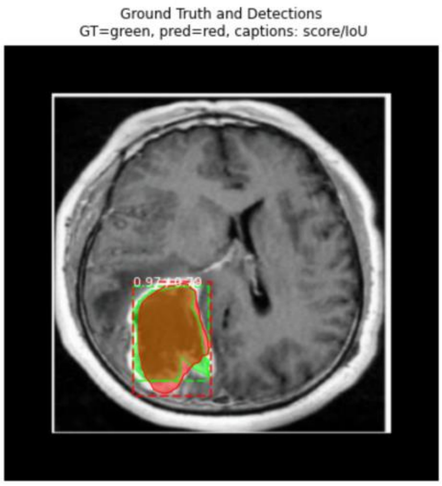
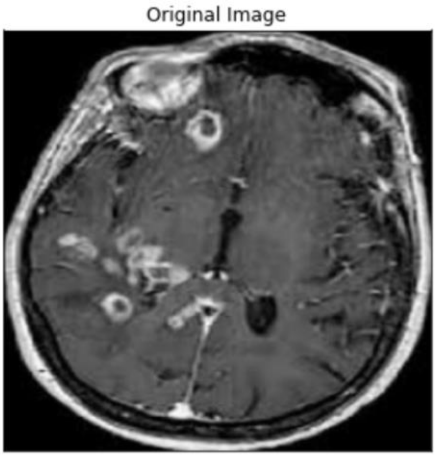


Fig: Original Image

Fig: Tumour detected Image

3. Mask R-CNN applied on Training dataset.



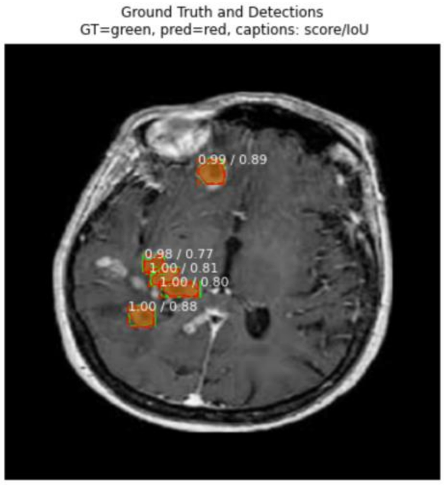
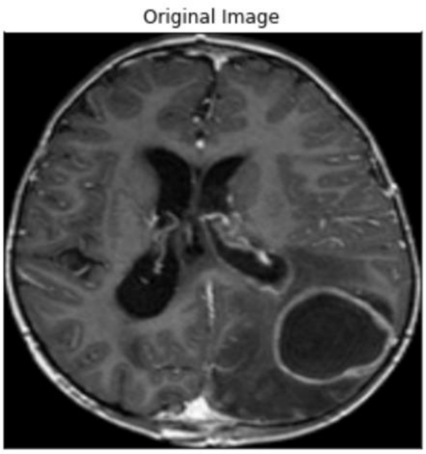


Fig: Original Image

Fig: Tumour detected Image



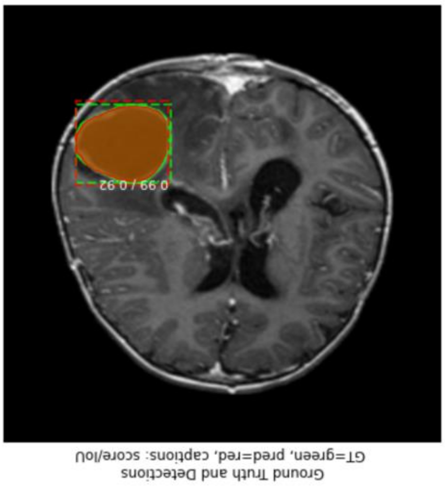


Fig : Original Image

Fig : Tumour detected Image

CONCLUSION:

Artificial Intelligence will surely help humankind in solving numerous trivial problems. This project mainly helps doctors to detect and localize the tumour in an MRI X-Ray in a very limited time and helps in acquiring precise results. Mask R-CNN performs instance segmentation and gives the location of the tumour for the provided images which saves time of the doctors while helping them navigate the tumour effectively and thereby decreasing the element of surprise while performing an operation or even helps avoiding the issue of going in blind surgically. We performed the project on a small image dataset, and it can be improvised for large image datasets and accurate results can be found.

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[3] https://action.cancer.ca/en/research/cancer-statistics/canadian-cancer-statistics

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[5] https://machinelearningmastery.com/how-to-perform-object-detection-in-photographs-with-mask-r-cnn-in-keras/

[6]https://www.google.com/search?q=MASK+R+CNN&rlz=1C1RXQR_enCA929CA929&sxsrf=ALeKk01vP_VSAI1pZGiF2RHasjthYMrkJg:1618600558596&source=lnms&tbm=isch&sa=X&ved=2ahUKEwim2s_6vIPwAhXS6J4KHd7XAOQQ_AUoAXoECAIQAw&biw=1536&bih=722#imgrc=NR17GqRwsHJbBM

[7] https://github.com/ruslan-kl/brain-tumor

[8] https://github.com/matterport/Mask_RCNN