Comparison of Mark RCNN from Canny edge detection techniques for brain tumor detection

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***Abstract*—Imaging technology in medicine made the doctors to see the interior portions of the body for easy diagnosis. It also helped doctors to make keyhole surgeries for reaching the interior parts without really opening too much of the body. CT scanner, Ultrasound and Magnetic Resonance Imaging (MRI) took over X-Ray imaging by making the doctors to look at the body's elusive third dimension. Image processing techniques developed for analyzing remote sensing data may be modified to analyze the outputs of medical imaging systems to get best advantage to analyze symptoms of the patients with ease.**

***Keywords*—Image Processing, Image analysis, applications, research.**

I. INTRODUCTION (*HEADING 1*)

In recent times, the introduction of information technology and e-health care system in the medical field helps clinical experts to provide better health care to the patient. This study addresses the problems of segmentation of abnormal brain tissues and normal tissues such as gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF) from magnetic resonance (MR) images using feature extraction technique and support vector machine (SVM) classifier [1, 2].

The tumor is basically an uncontrolled growth of cancerous cells in any part of the body, whereas a brain tumor is an uncontrolled growth of cancerous cells in the brain. A brain tumor can be benign or malignant. The benign brain tumor has a uniformity in structure and does not contain active (cancer) cells, whereas malignant brain tumors have a nonuniformity (heterogeneous) in structure and contain active cells. The gliomas and meningiomas are the examples of low-grade tumors, classified as benign tumors and glioblastoma and astrocytomas are a class of high-grade tumors, classified as malignant tumors.

In this study, different magnetic resonance imaging (MRI) sequence images are employed for diagnosis, including T1-weighted MRI, T2-weighted MRI, fluid-attenuated inversion recovery- (FLAIR) weighted MRI, and proton density-weighted MRI. The detection of a brain tumor at an early stage is a key issue for providing improved treatment. Once a brain tumor is clinically suspected, radiological evaluation is required to determine its location, its size, and impact on the surrounding areas. On the basis of this information the best therapy, surgery, radiation, or chemotherapy, is decided. It is evident that the chances of survival of a tumor-infected patient can be increased significantly if the tumor is detected accurately in its early stage [9]. As a result, the study of brain tumors using imaging modalities has gained importance in the radiology department.

II. IMAGE PROCESSING

A. Introduction

An image may be defined as a two-dimensional function, f(x, y), where x and y are spatial (plane) coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When x, y, and the amplitude values of f are all finite, discrete quantities, we call the image a digital image. The field of digital image processing refers to processing digital images by means of a digital computer. Note that a digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are referred to as picture elements, image elements, pels, and pixels. Pixel is the term most widely used to denote the elements of a digital image. Vision is the most advanced of our senses, so it is not surprising that images play the single most important role in human perception. However, unlike humans, who are limited to the visual band of the electromagnetic (EM) spectrum, imaging machines cover almost the entire EM spectrum, ranging from gamma to radio waves. They can operate on images generated by sources that humans are not accustomed to associating with images. These include ultrasound, electron microscopy, and computer-generated images.

B. Mask R-CNN

Mask RCNN is a deep neural network aimed to solve instance segmentation problem in machine learning or computer vision. In other words, it can separate different objects in a image or a video. You give it a image, it gives you the object bounding boxes, classes and masks.

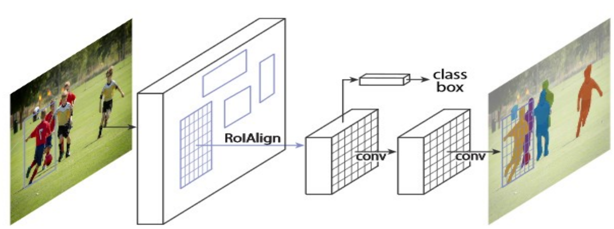

Figure 1. The **Mask R-CNN** framework for instance segmentation.

There are two stages of Mask RCNN. First, it generates proposals about the regions where there might be an object based on the input image. Second, it predicts the class of the object, refines the bounding box and generates a mask in pixel level of the object based on the first stage proposal. Both stages are connected to the backbone structure.

One advantage of Mask R-CNN is that it gives both bounding box and semantic segmentation,this allows for a multi-stage approach for semantic segmentation using the same architecture. The firststage is analyzing the image with its original view/zoom scale, and the second stage focuses on theoptic nerve head and zooming into it for further analysis.

C. Canny edge detection

The canny edge detection algorithm was proposed to enhance the edge detection process. Three important criteria were taken into consideration for this purpose. The first and most important criterion was to detect all the important edges in the source image. This means the goal was to lower theerror rate. The second criterion was that the edge points to be detected as close as possible to the true edge, also called as localization. A third criterion was not to have more than oneresponse to a single edge. The first two were not significant enough to remove the possibility of more than one response to an edge due to which the third one was implemented. The Canny edge detector was thus implemented on these criteria. It first smooths the image to eliminate noise. Then the image gradients are calculated to point out those regions where the gradient difference is maximum, which have high spatial differences. Finally, it then tracks along these regions and discards any pixel that weakly defines an edge (non-maxima suppression) in order to make the edges thinner. To further reduce the gradient array, it performs hysteresis whichtracks along the remaining pixels that have minimum gray level values but have not been suppressed

fig2. Canny edge approch applied to a photograpgh

III. IMPLEMENTATION

A. Pseudocode

1) Clone the Mask R-CNN repository and Brain MRI scan as inputdata.
2) Creating the directory structure of the inputdata.
3) Configuration for training on the brain tumordataset.
4) Build the custom brain MRI dataset
5) InitializetheMaskR-CNNmodelfortrainingusingtheConfiginstancethatwecreatedand load the pre-trained weights for the Mask R-CNN from the COCO data set excluding the last fewlayers.
6) Load the dataset and train your model for 15 epochs with the Learning rate as0.001
7) Recreate the model in inference mode
8) Now build functions to display theresults.
9) Test your model prediction on the validationset:

IV. RESULT

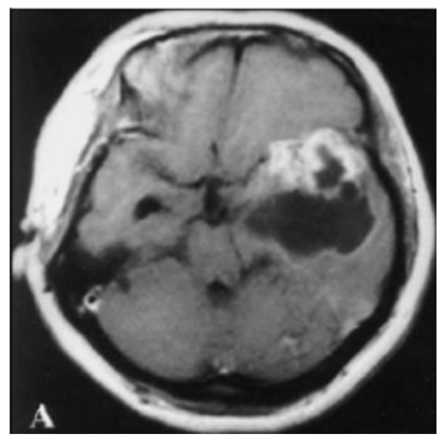

FIG3. (A) ORIGINAL IMAGE

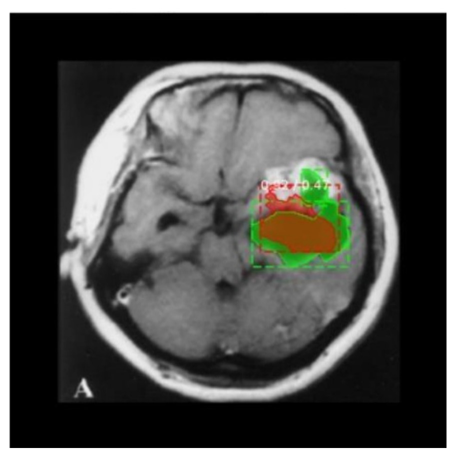

FIG 3. (B) OUTCOME AFTER PROCESSING

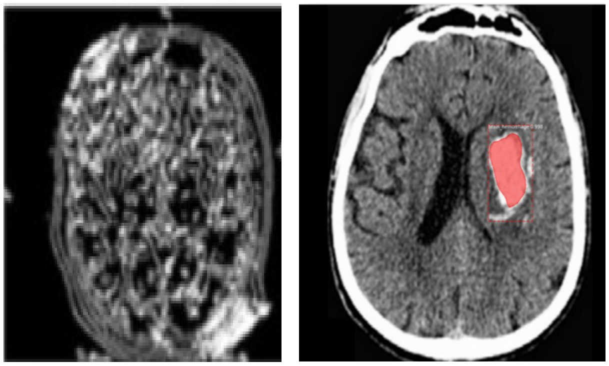

FIG 3. (A)CANNY EDGE DETECTION (B) MAK RCNN

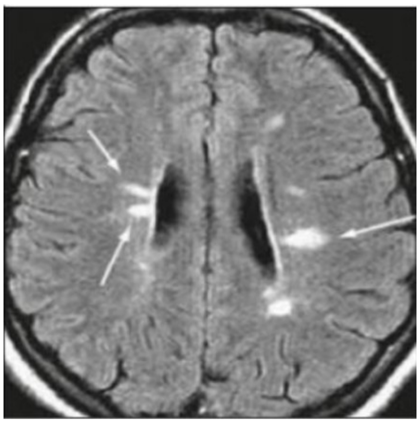

FIG 4. A THE ORIGINAL IMAGE BEFORE PRECESSING

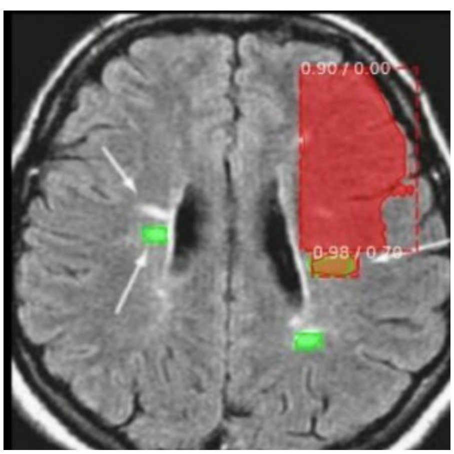

FIG 4. B THE IMAGE AFTER PROCESSING IN MARK RCNN

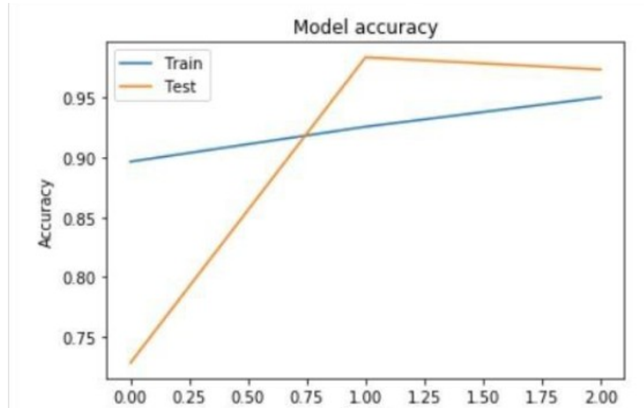

FIG 5. (A) MODEL ACCURACY GRAPH OF MARK RCNN

FIG 5. (B) MODEL ACCURACY GRAPH OF CANNY EDGE DETECTION

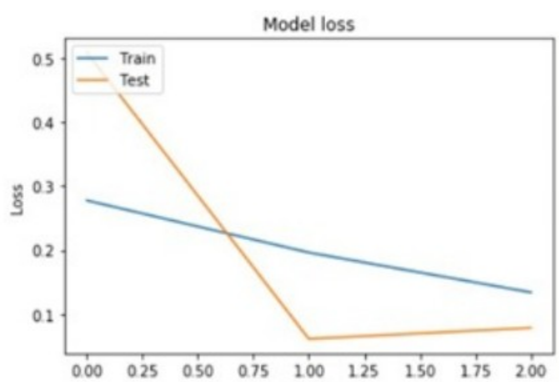

FIG 6. (A) MODEL LOSS GRAPH FOR MARK R-CNN

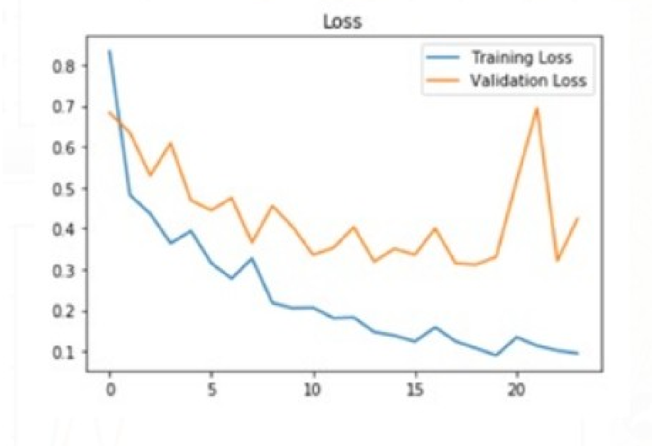

FIG 6. (b) MODEL LOSS GRAPH OF CANNY EDGE DETECTOPM

V. CONCLUSION AND FUTURE WORK

In the study we found that there are many segmentation and image processing techniques that can be used to detect brain tumours from MRI images, we would like to conclude that out of the two MARK RCNN and Canny edge detecton, Mark RCNN is found to have better accuracy and has less loss percentage as compared to the canny edge technology. In terms of the training time for the model canny edge is found to be better then Mark Rcnn.

In the future work, we would like to add more classifier and feature selection techniques to the comparison . We would also be looking into finding the type of brain tumours using all the techniques and using them as a comparison critaria too.

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