DEEP LEARNING FOR AUTOMATED STAGING OF RECTAL CANCER AND LYMPH NODES ON MRI

OCTOBER 24, 2021

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Table of Contents

Background

The cancer that affects the rectum or colon, also called bowel cancer, is third most common in men and second most prevalent cancer in women. An intrapelvic recurrence followed by the primary rectal resection, is a major complication with a recurrence rate of 50% [2].

St Vincent's Hospital

The St Vincent's Hospital, operated by St Vincent's Health service, is one of the well-known hospitals in Melbourne. The hospital's area of expertise includes cardiology, cancer, neurosurgery, heart-lung transplantation, and others. The first hospital was constructed in 1857 in Sydney by the Sisters of Charity and today they have 6 public hospitals, 10 private hospitals, and 20 aged care facilities. It is Australia's largest not-for-profit health and aged care provider [23]. Expertise from the Radiologists was very much helpful on understanding the concepts behind rectal cancer, diagnosing the rectal cancer and the MRI images. During this project the team has the expertise guidance from Dr Mark Page, Radiologist at St Vincent's Hospital.

Diagnosis of colorectal cancer

Numerous factors including age, family history, medical tests, and symptoms are used to determine which tests will be performed to diagnose colorectal cancer. The following tests are more common [3]:

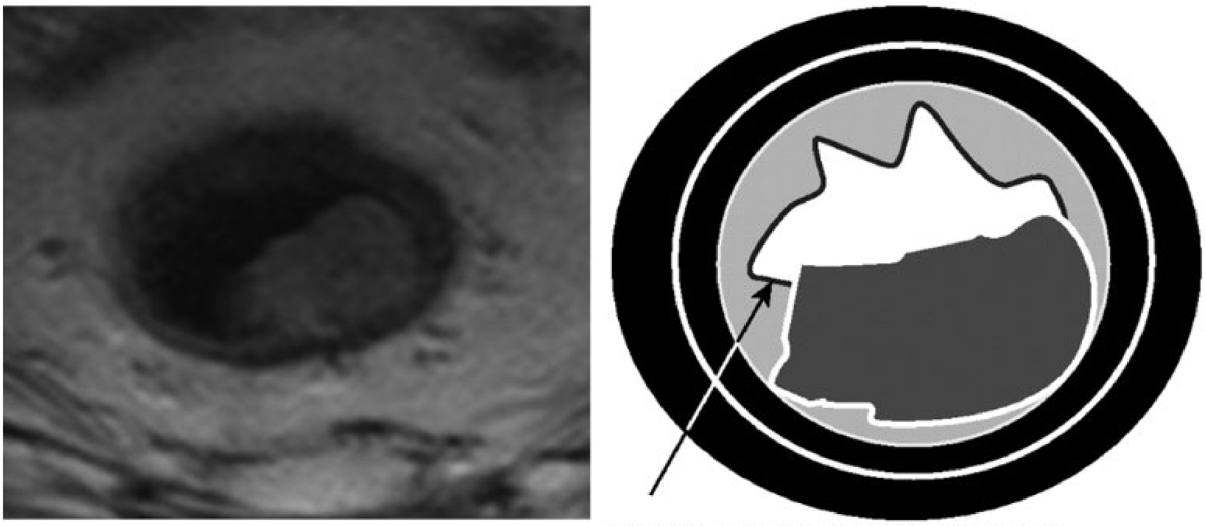
1. **Colonoscopy:** A long elastic tube (colonoscope) with a camera mounted at the top is inserted into the rectum while the patient is sedated to examine the inner region. This test can indicate the presence of cancer tissues, but further tests are required for a complete diagnosis.
2. **Biopsy:** It is a process of examining the extracted cancer tissues with a microscope. It is needed to classify the cancer tissues and determining treatment options.
3. **CT and PET-CT:** Computed Tomography (CT) scan entails X-rays taken from various angles to create a detailed 3-dimensional image of the affected regions. These images are used to calculate the size of the tumour and discovering its proliferation. In a Positron Emission Tomography (PET) CT scan, a small quantity of radioactive sugar is injected into the patient. As the cancer cells utilize more energy, it absorbs more amount of this radioactive sugar. A scanner detects the radioactive sugar and engender images of the tumour.
4. **Magnetic resonance imaging (MRI):** Both MRI scans and CT scans have similar applications. Instead of using X-Rays, an MRI scan uses a strong magnetic field to generates more detailed image of the body.
5. **Ultrasound:** It utilizes sound waves to generate pictures of the internal organs and detects the location of cancer alongside of its metastasis. However, it cannot identify the cancer tissues accurately, that are beyond the pelvis.

Although there are numerous ways to diagnose cancerous cells, the problem is resolved using the data from MRI images. As a result of the superior soft tissue contrast resolution, the Pelvis with distension of the rectum is examined by high-resolution MRI by positive contrast agent, to detect rectal cancer that are stated locally [18].

TNM Classification of Rectum

According to the clinical guidelines report of European Society for Medical Oncology (ESMO), the TNM classification of rectal cancer is illustrated in figures 7a & 7b as follows [4].

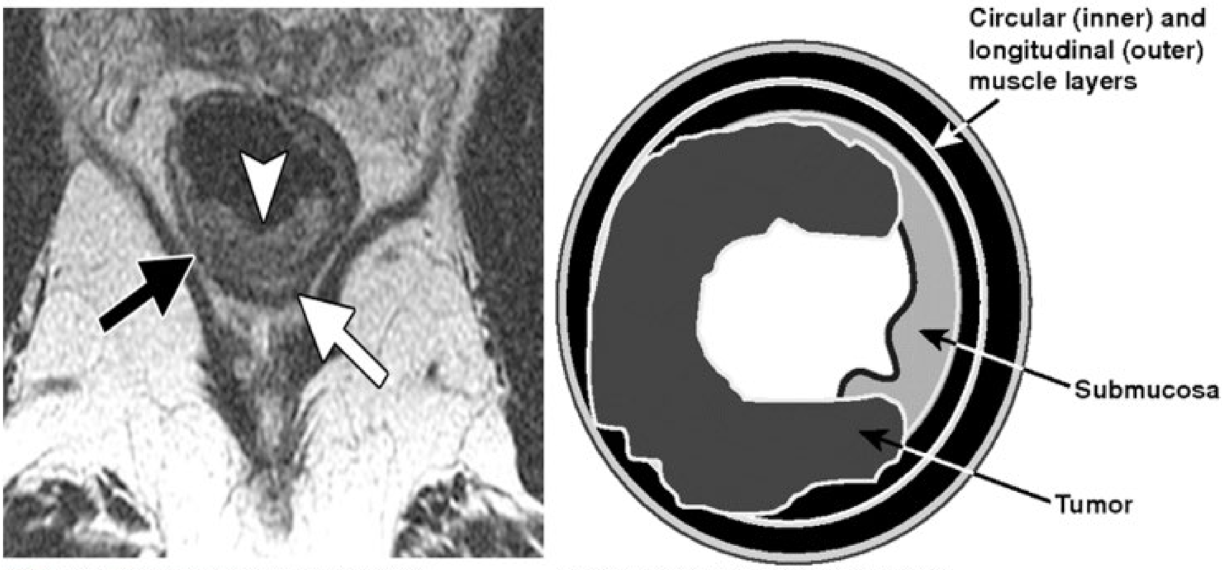
T1



Taylor FG, et al. AJR Am J Roentgenol. 2008 Dec;191(6): 1827-35.

Figure 1: *Staging T1 cancer: It is clearly visible that the cancer spread is within the Rectal wall [2, slide 19]*

T2



Kaur H, et al. Radiographics. 2012 Mar-Apr;32(2): 389-409.

Taylor FG, et al. AJR. 2008 Dec;191(6):1827-35.

Figure 2: *Staging T2 cancer: It is clearly visible that the cancer spread on the Rectal wall [2, slide 21]*

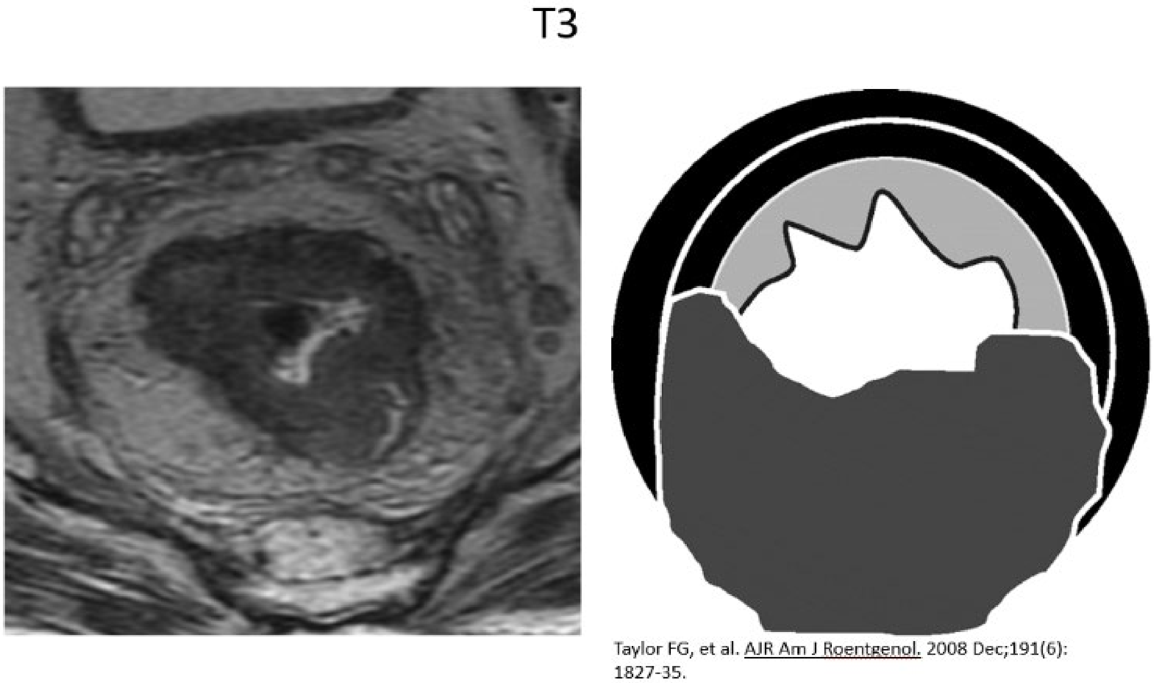


Figure 3: *Staging T3 cancer: It is clearly visible that the cancer is spreading outside the Rectal wall [2, slide 23]*

Treatment for each stage

Rectal cancer is divided into 4 major stages and the treatment plan changes accordingly to the table [2].

Stage	**Treatment**	
Stage 1	Transanal Excision	To treat the initial stages of rectal cancer, surgery is necessitated with the removal of tumour cells.
Stage 2	Total Mesorectal Excision	For the stage 2 cancer, the common procedure is to remove a significant amount of bowel around the tumour cell.
Stage 3	Preoperative chemoradiation and TME	Combination of different therapies including chemotherapy, radiotherapy, before surgery, is recommended for treating stage 3 cancer.
Stage 4	Preoperative chemoradiation and exenteration	Pelvic exenteration surgery followed by the Chemoradiotherapy is a common treatment for stage 4 cancer.

Identification of rectal cancer

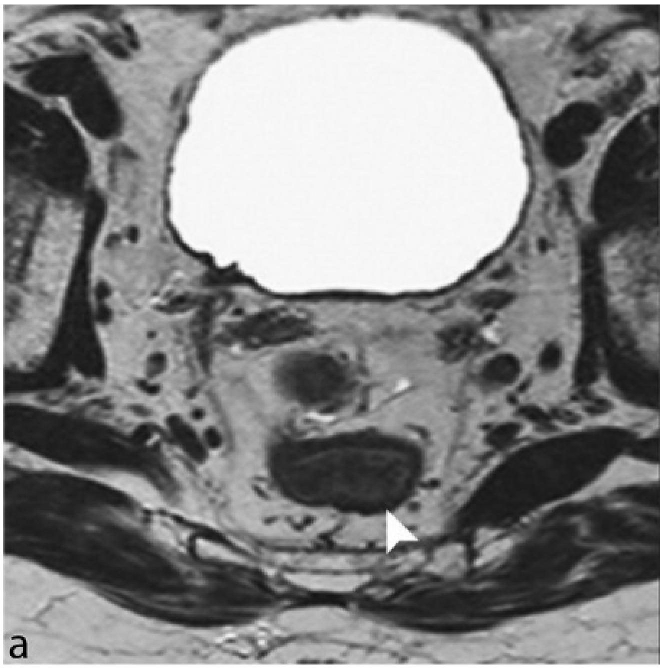
The radiologists will identify location of the tumour by looking at the T2 weighted sagittal view image. Once the location is identified, the T2 weighted axial view image (figure 4a) and Diffusion Weighted Image (DWI) (figure 4b) will aid in understanding the spread of the tumour.

Axial T2-Weighted Imaging

One of the basic pulse sequences on MRI is T2 weighted image, where the inflammation part is brighter. The axial view is a sliced-up view of human body. Since the rectum is a tube-like structure, this view helps in procuring better knowledge of the tube's interior [5, 9].

Diffusion Weighted Imaging (DWI)

In the diffusion weighted image, the highly cellular tissues such as swelling/inflammation will be brighter whereas the fluid substances will be darker. Thereby, the DWI is employed to localizing the tumours [5].



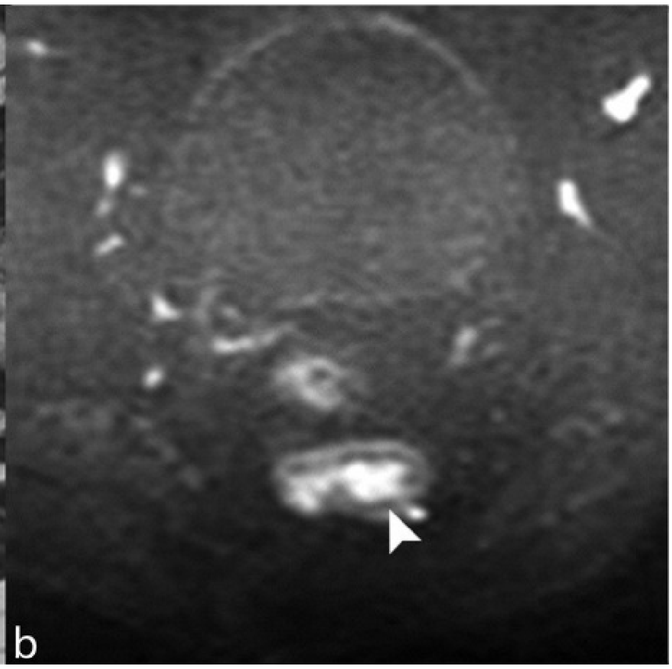


Figure 4a: *T2 Weighted Axial View Image [5, fig 2]*

Figure 4b: *Diffusion Weighted Image[5, fig 2]*

Lymph Nodes

Lymph nodes help in understanding the spread of cancer cells in a better way and hence radiologists track the lymph node system to identify the number of affected lymph nodes. More than 60% of the lymph nodes are less than 5mm in size and it is difficult to localize them in the MRI images [6, 7].

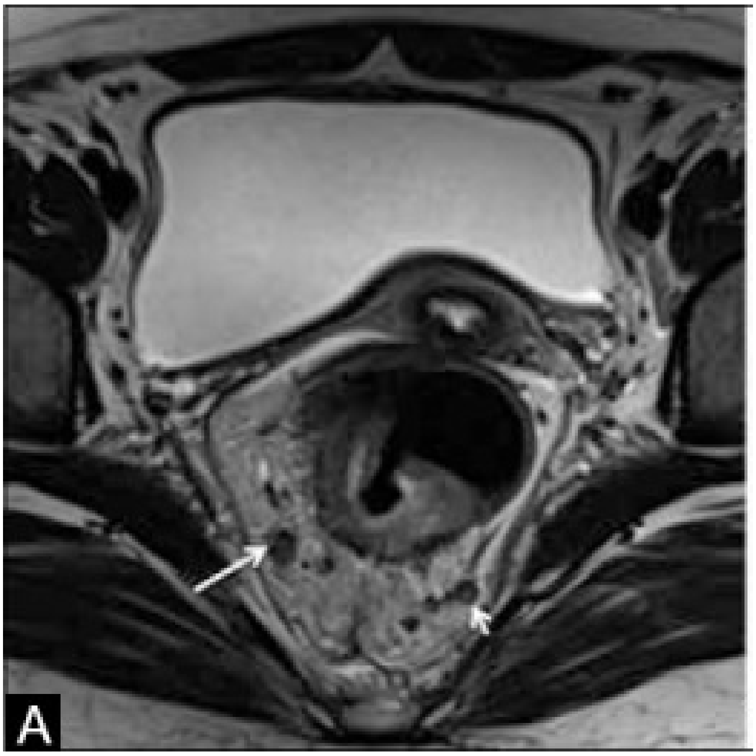


Figure 5: *Lymph Node: One on the left side (long-arrow) is approx. 5mm in size and the other on the right side (short-arrow) is <3mm in size. [7, fig 17]*

Challenges in detection of Cancer cells and Lymph nodes

One of the major challenges occurs while staging the T3a cancer. It is difficult to identify whether the cancer cell has spread through the mesorectal fascia, as the size of the tumours might be less than 5mm (figure 6a). Similarly, staging of T4a cancer is also challenging, as radiologists require accuracy in identifying the other organs which are affected by the tumour (figure 6b). It is also tedious task to identify the spread of tumour after chemo-radiotherapy treatment, as the occurrence of tumour might be reduced [8].

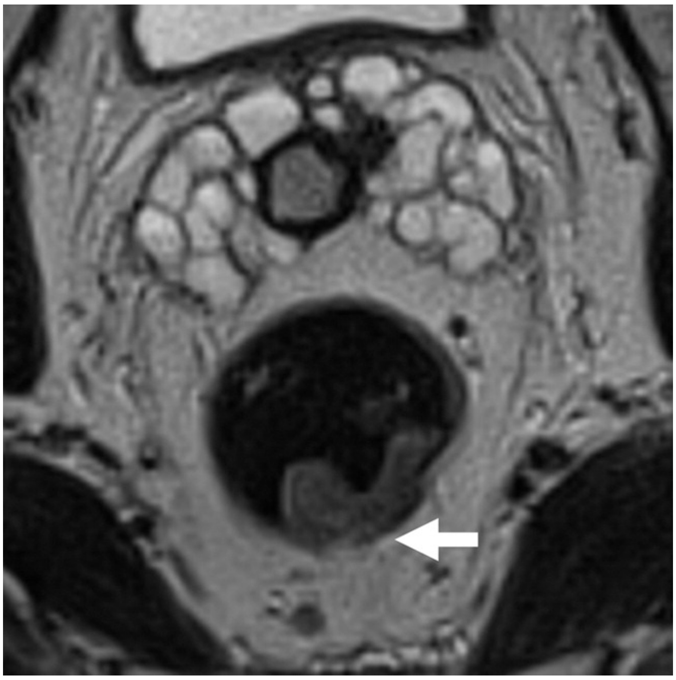


Figure 6a: *Subclassification of T3a cancer: tumour spread is less than 1mm (arrow) [8, fig 5a]*

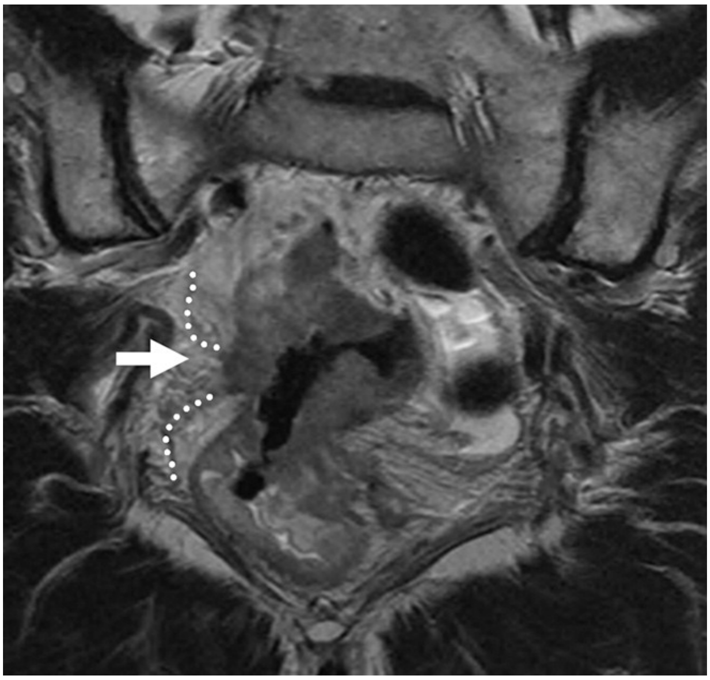


Figure 6b: *Subclassification of T4a tumour: other organs is partially affected by the tumour (dotted line) [8, fig 6]*

Aims of the Project

Initial Project Aims

The project aims to build a system to support radiologist to determine the course of action with patients with rectal cancer divided into two main goals.

- Distinguish T2 from T3 tumours to aid radiologist determine if surgery or chemoradiotherapy are required, respectively.
- Determine if the cancer has affected lymph nodes.

To reach these goals, the team had planned the next deliverables.

- Prepare the database / Build the dataset.
- Image set suitable for the task.
- Develop the data handling pipeline.
- Develop the Machine Learning System to the classification task (distinguish T2 from T3 tumours).
- Develop the Machine Learning System to determine if cancer has affected lymph nodes.

Current Project Aims

Project's aims did not change

- Distinguish T2 from T3 tumours to aid radiologist determine if surgery or chemoradiotherapy are required, respectively.
- Determine if the cancer has affected lymph nodes.

After the training of the deep neural network in charge of predicting the course of action, the team found out the presence of overfitting and poor generalisation on unseen MRI images for two reasons.

- The size of the data set.
- Extraction of non-relevant features.

Given the time left for the project and local restrictions due the covid pandemic, extracting more and better samples was not a feasible task. However, the model could be guided by exclusively giving the region of interest. For instance, the following images belong to the same MRI. On the left side, there is a complete MRI that contains the rectum and other body parts. On the right side, there is an ideal segmentation of the rectum. Even though that the image on the left has the region of interest (the rectum) it also has parts not relevant to this problem causing extraction of non-appropriate features to determine the course of action, thus, misguiding the model.

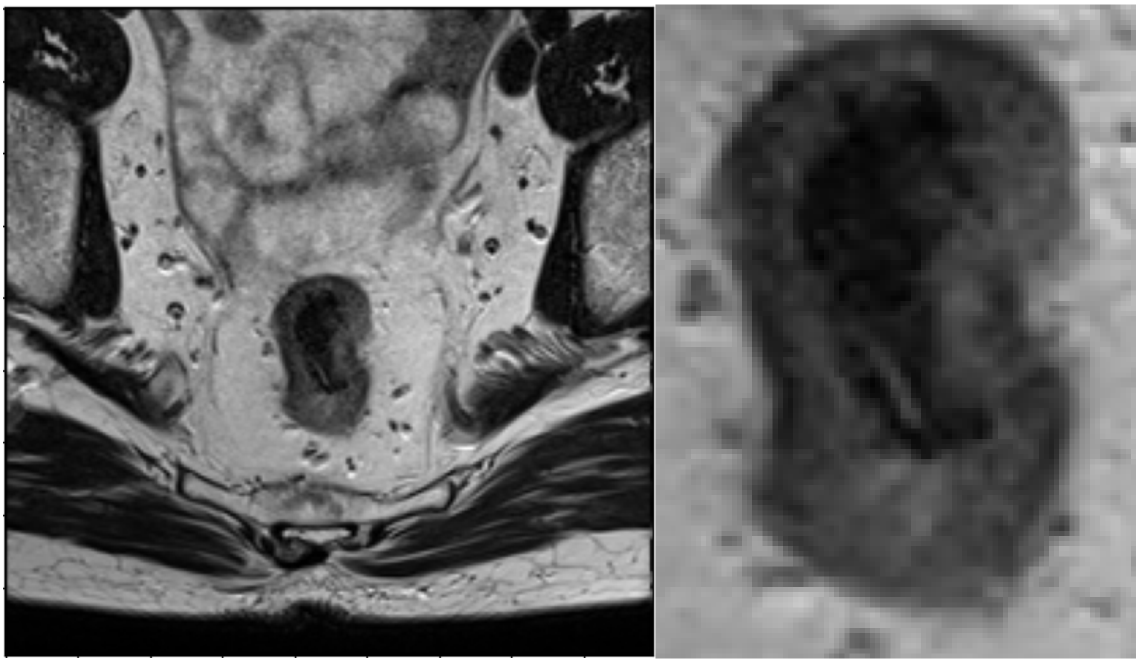


Figure 7: Complete MRI vs Segmented Rectum

As a result, the team decided to build a **tool** that helps to **annotate the images** and improve the quality of data. This deliverable is called **"Rectum Segmentation"**. Also for the lymph node extraction, it was identified that the given data is insufficient to develop a model. The vision technique is utilized by the team to obtain similar regions of the lymph node, by which the annotation can be executed. In addition, another tool is built to annotate the regions of lymph nodes, and this deliverable is termed as the **"Lymph node annotation tool"**.

The final deliverables to the project are:

- The dataset.
- Data handling pipeline (model training for course of action).
- Segmentation tool.
- Lymph Node annotation tool.
- Course of action predictor.
- User manual.
- Developer manual.

Approach / Methodology

Data

The first step taken after digitizing the data was data analysis. After a knowledge transfer session with the radiologists from St.Vincent's hospital, it was recognized that axial images which provide an extent of cancer spread across the rectum wall is crucial in differentiating stages of cancers from MRI scans. Additionally it was learnt that T2 Small Field of View(FoV) and DWI images are the two types of scan sequences used by radiologists to recognise cancer cells as T2 and DWI image provide good resolution and contrast between normal rectum tissue, fat region and cancer cells. Since all the scan sequences are in DICOM image format, a python library known as PyDiCOM was used to extract details from each sequence. It was observed that the data provided to the team had scans for a total of 114 patients. Among the 114, only 76 patients had DWI axial MRI scans while there were 87 patients with axial T2 weighted small(160) FoV scans.

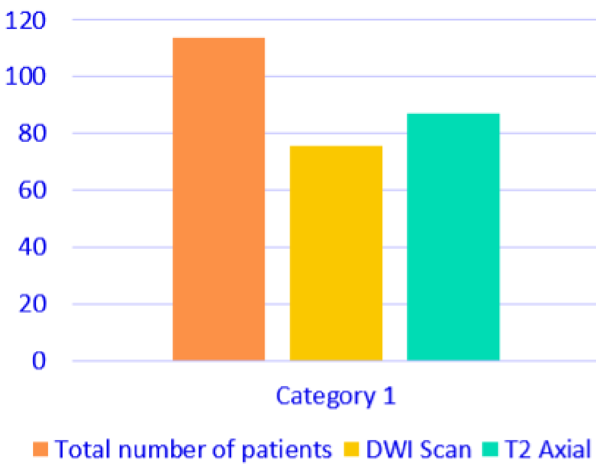


Figure 8:

Directory Structure

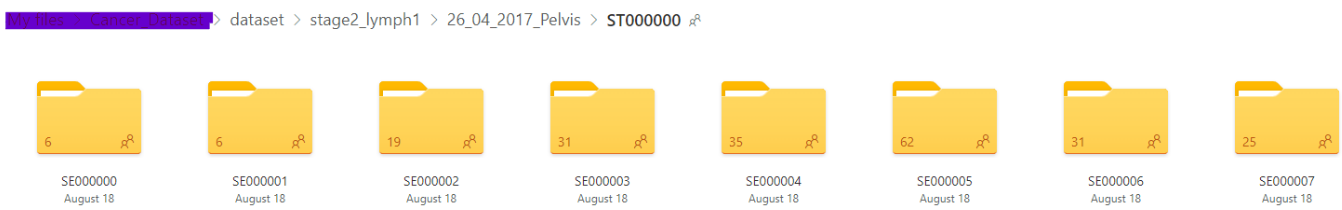


Figure 9: *Original directory structure*

Renaming the directory

It is hard to comprehend the actual sequence of the data by taking a glance at the directory structure. To solve the issue, the data from T2_160_FOV and the T2_DIFF_FOV are crucial, and hence a tool is built to rename the sequence based on the FOV it was taken. The renaming is implemented by parsing the metadata information from the Dicom image using the Pydicom package.

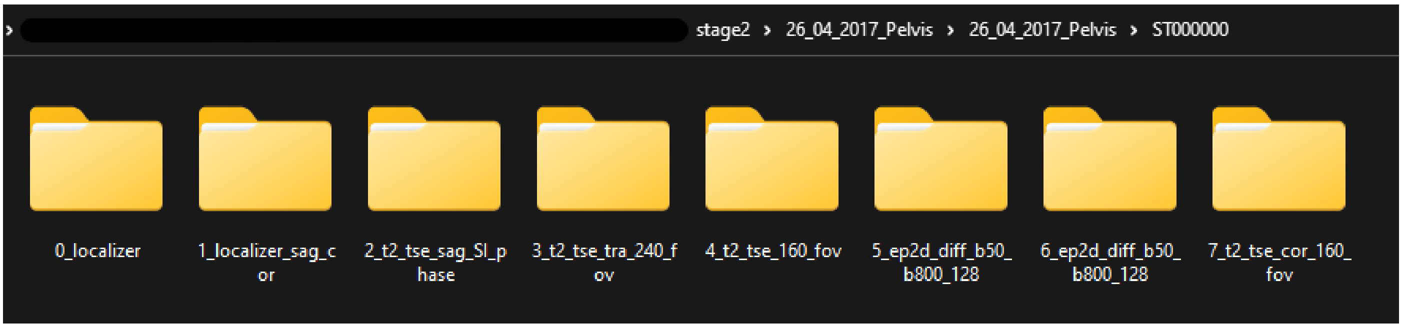


Figure 10: *Renamed directories*

Rectum Segmentation:

Introduction

Image segmentation is an important step to extract the area of interest and to remove non-essential information from the images. The patient's MRI not only contains the rectum but the surrounding regions and organs as well like bladder and seminal vessels (as shown in figure 11). For identifying cancer and lymph nodes, the surrounding regions needed to be cropped out so that the Deep Learning models can focus on the rectum.

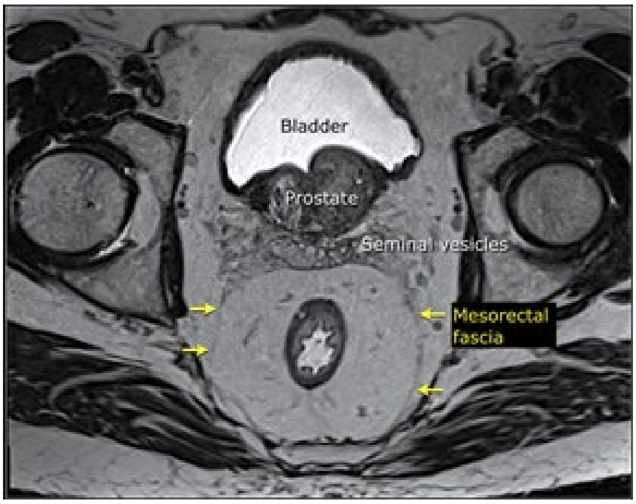


Figure 11: *Rectum and its surrounding regions [22]*.

Approach

The images are extracted from the DICOM file using the python pydicom package. The algorithm works on these extracted images using cv2 module [19] and PIL Image library [20].

Cropping the image

The first step involves cropping out the region where the rectum is most likely to be present. It has been observed that the rectum is mostly present in the lower half of the MRI images. So, for the T2_160_FOV images which are of dimension 256*256, the crop size is chosen to be 200*200 (from coordinates (100,100) to (300,300)), and for the T2_DIFF_FOV images which are of dimension 128*128, the crop size is 70*70 (from coordinates (50,50) to (120, 120)). Using these cropping dimensions, the lower half of the original images are being cropped.

Finding the rectum

The second step involves finding the rectum in the cropped image. The rectum usually has a circular shape and by using this knowledge we can search for multiple circular shapes in the cropped image by using skimage library in python [21]. We can now find the average pixel values inside all these circular regions and set a threshold range which will eliminate the wrong regions.

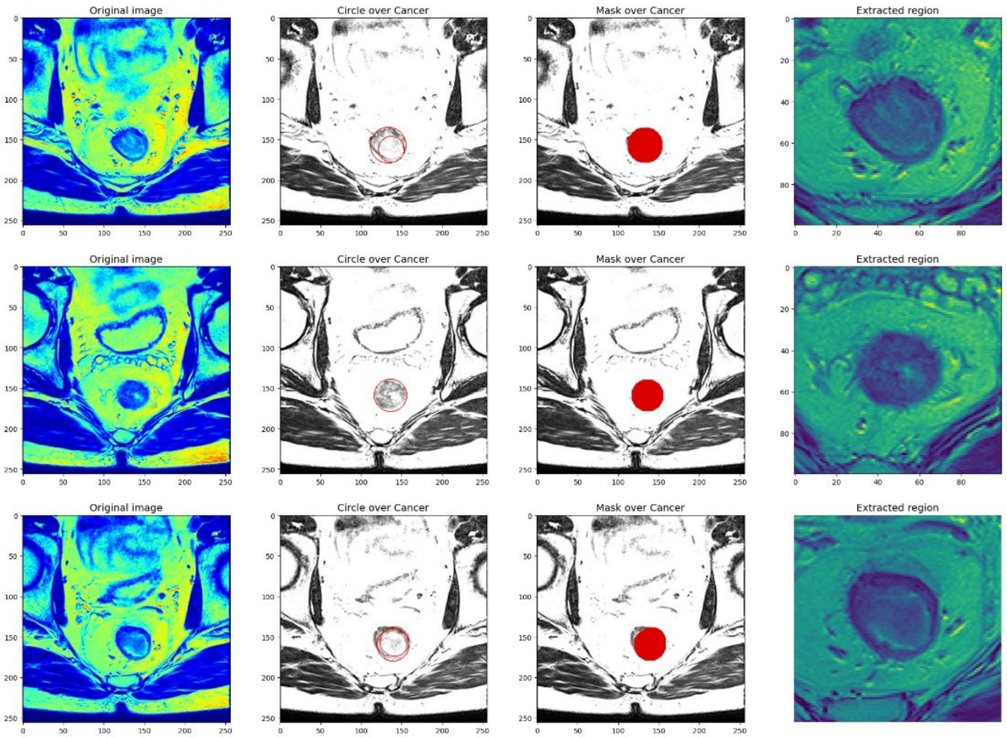


Figure 12: Results after applying segmentation algorithm. The first column shows original MRI image. The second and the third columns shows the rectum location and the last column shows the cropped rectum region.

Improving the algorithm

The overcome the challenges faced by the initial algorithm (specified in Results, Evaluation & Analysis section), the following improvements are added to the algorithm:

1. we have stored the last known rectum location and used it in the upcoming slide where the algorithm is unable to find rectum. In the figure 13, we can see that previously, the algorithm found rectum only in 1101 images out of 3311(actual image count). After using last known location of rectum, additional 1770 images are included.
2. another set of refined datasets is also generated only by cropping the image between start point (40,100) and end point (200,220), which mostly contained the rectum region. If the original algorithms still fail to identify correct rectum region, then the images from this dataset can be added to the original dataset.
3. A user interface using the Tkinter package in python is also developed to assist the user in finding rectum and saving the cropped image.

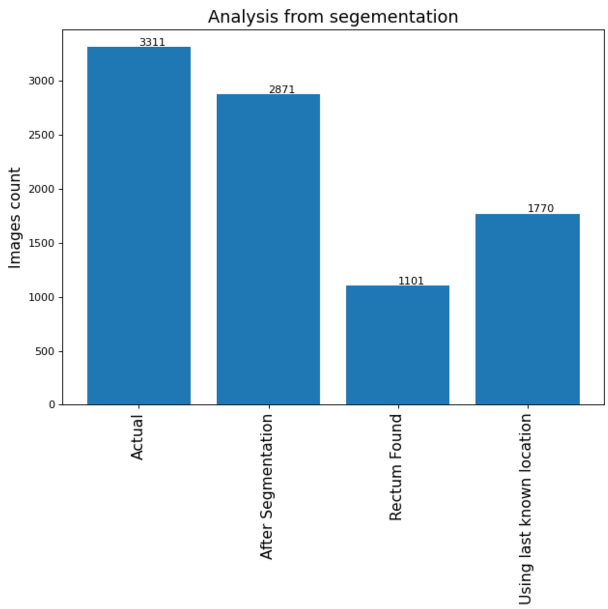


***Figure 13**: Analysis of segmentation algorithm for T2_160_FOV*

GUI for identifying rectum

A Graphical User Interface (GUI) is created to help users identify the rectum region, segment it, and save the results. The following figure shows the GUI for segmentation. It has the following functionalities:

1. The user can select the whole folder where the Dicom files are stored and can browse through each slice inside the folder.
2. The user can specify the image name and the folder where the cropped image has to be stored. By default, it will be stored in 'new_folder' with the slice index as the image name.
3. The segmentation algorithm will assist the user in identifying the rectum regions. It will al draw a circle around the rectum and display the cropped image containing the rectum.
4. If the generated results are incorrect, then the user can click on the original image at the location of the rectum, and the cropped image will be updated with the selected region.

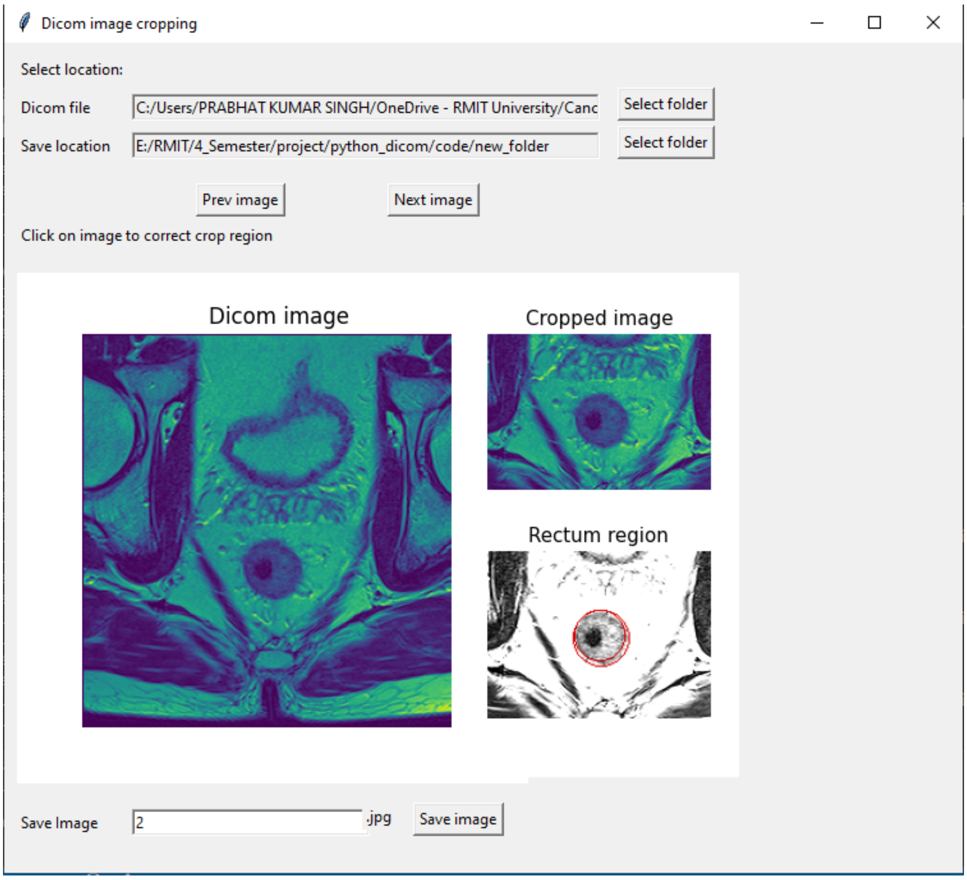


Figure 14: *GUI for assisting image segmentation*

Course of action predictor

Problem definition

The main difficulty for radiologist is to distinguish between stage 2 and stage 3 of cancer (T2 & T3) that is the separation line of treatment. For instance, if a patient is in stage 2 or **below**, the course of action is surgery to extract the tumour. However, if it is stage 3 or **above**, it is compulsory to shrink the tumour using radiochemotherapy before the extraction to reduce the chances of recurrence. The stages were divided into 2 groups or course of actions, the ones that can proceed with surgery (T1, and T2) and the ones that need regression treatment (radiochemotherapy) before extraction (T3 and T4) The goal of the predictor is to determine which action take given an MRI image.

Data selection

The dataset comprises mixed type of image with different planes, field of views and resolutions. For example, there are transversal, sagittal, and frontal planes

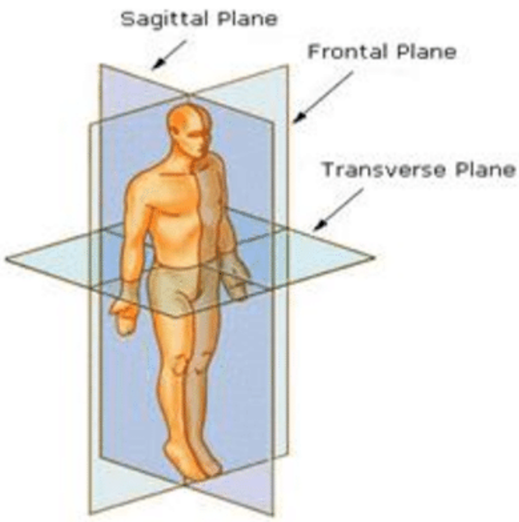


Figure 15: *Types of planes, taken from [11]*

The type of images that facilitate the tumour identification are T2 weighted MRI, where two types of tissue are bright, fat and water [12], images taken from a transversal plane, and with a field of view of 160. There are only 101 records of MRI available with these characteristics. Usually, to train a neural network from scratch thousands or even millions of images are used depending on the problem, some of the strategies to handle situations where there is not enough data are using transfer learning and data augmentation.

Transfer Learning

Resnet are a set of well-known deep neural networks with depth of up to 152 layers [13] that were trained using the ImageNet dataset [14] The idea of transfer learning is to use an existing trained network and use its knowledge of feature extraction to process images. Technically, this process is done by detaching the last layer that does the classification, that for ImageNet was to classify 1000 images, attaching a layer with the required problem to solve, in this case binary classification (surgery or radiochemotherapy), and finally, training ONLY the desired layers. However, within the ImageNet dataset there are not MRI images, therefore it is possible that the model backbone (Resnet) is not good enough extracting key features to solve this problem. Nevertheless, it was the best approach given the circumstances.

Data Augmentation

Data augmentation means that the current images will go through a process of transformations to create new instances that allows to increase the initial data. Such transformations include clipping, cropping, flipping, re-colouring, rotating, resizing, etc. No all the transformations are relevant to the problem, in this case, flipping an image upside-down does not make sense since the images provided to the detector always have the same orientation.

Image Transformation

For image augmentation 3 techniques were used: resizing, a sliding window technique to create 3 channels, and cropping.

Resizing

Resnet input is an image of 224 x 224 dimensions (width and height) since the images came in different shapes, a resizing transformation was required. The following image depicts the correct dimensions.

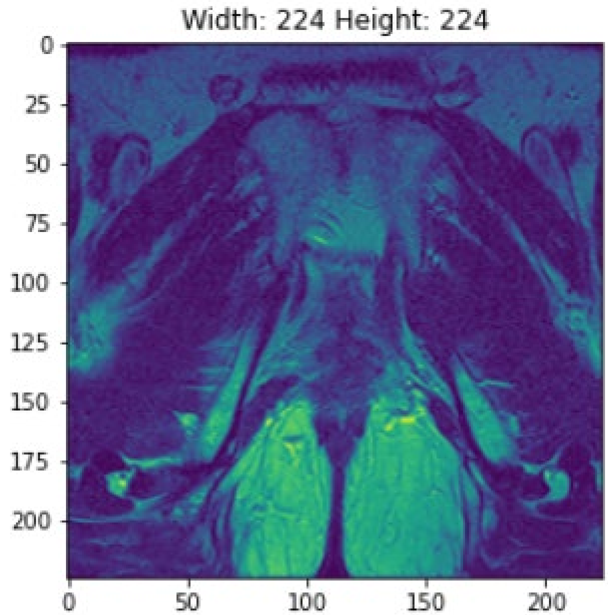


Figure 16: MRI resized

Channels

Images usually come with 3 channels red, green, and blue (RGB) or 4 channels (RGB plus alpha/transparency channel) After reading the MRI images there are not explicit dimensions for the channels what gave the green colour appearance that can be seen on the following image, a comparison between MRI and JPG formats.

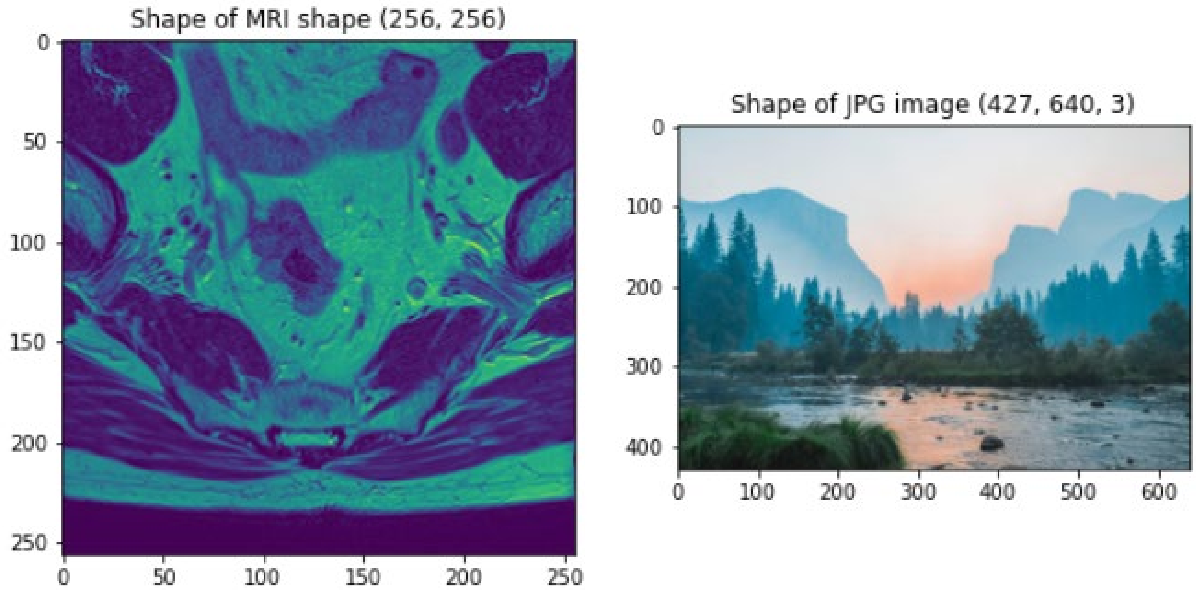


Figure 17: Channels comparison

Patient data came with multiple transversal plane slices (from patient top to bottom or vice-versa) having multiple slices allowed the use of a sliding window to combine multiple sets of 3 images and create a new image instance with 3 channels. For example, take slice 1, 2 and 3 and put them in the respective channels 1, 2 and 3. Then take slice 2,3 and 4 and do the same, then slice 3,4 and 5 and continue the process until reach the final slice like a sliding window of size 3. The following image illustrate the result of an instance of this process.

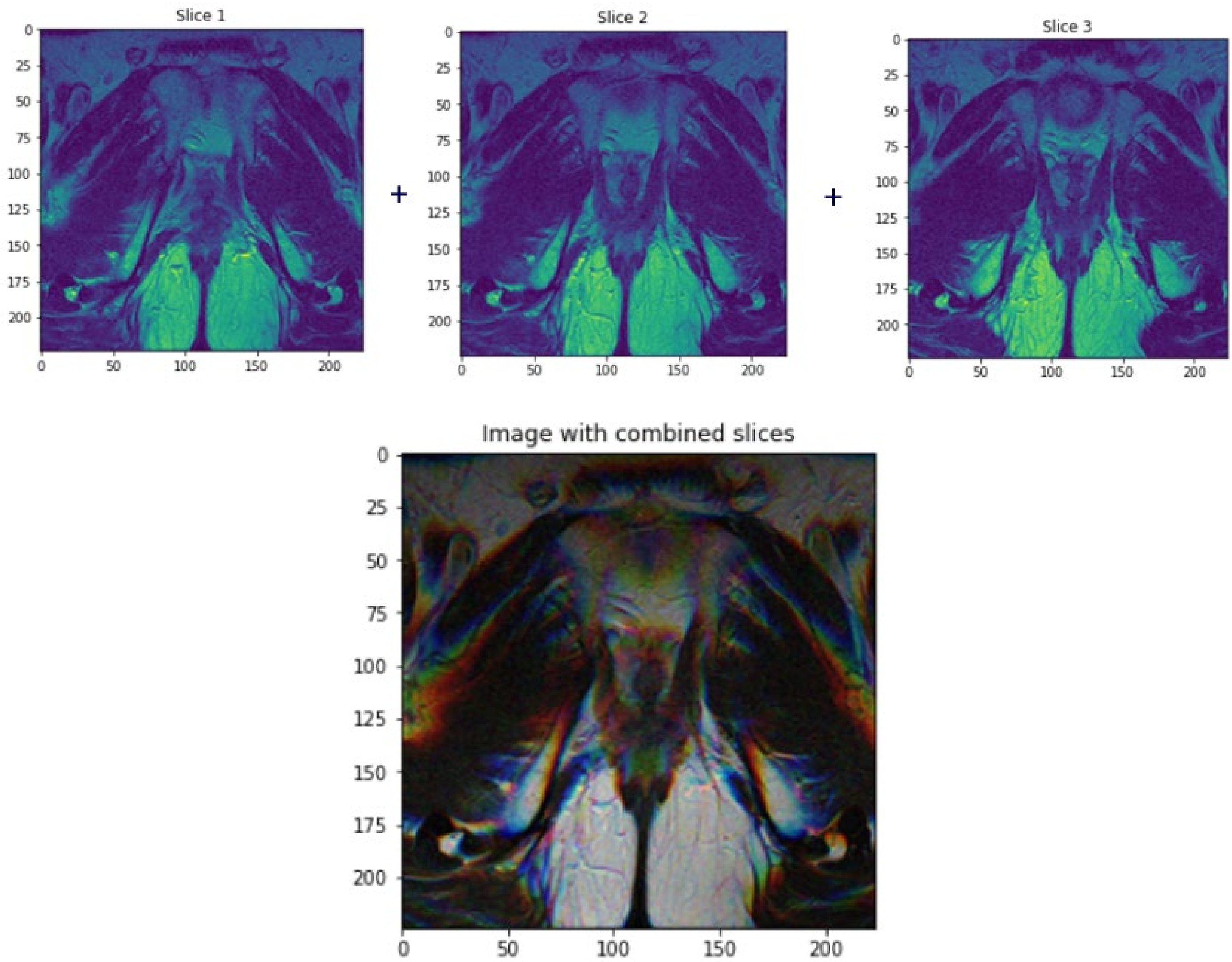


Figure 18: Combining slices

By doing this combination and the resizing process the result are instances with 224 x 224 x 3 (width, height, channels) dimensions, the required input for ResNet.

Cropping

An empiric cropping was performed starting from pixel 50 and finishing at pixel 170, this gave an improved segmentation of the rectum that led to better identification of the key features, therefore, an increase on the accuracy. The following image shows before and after cropping and its respective resizing.

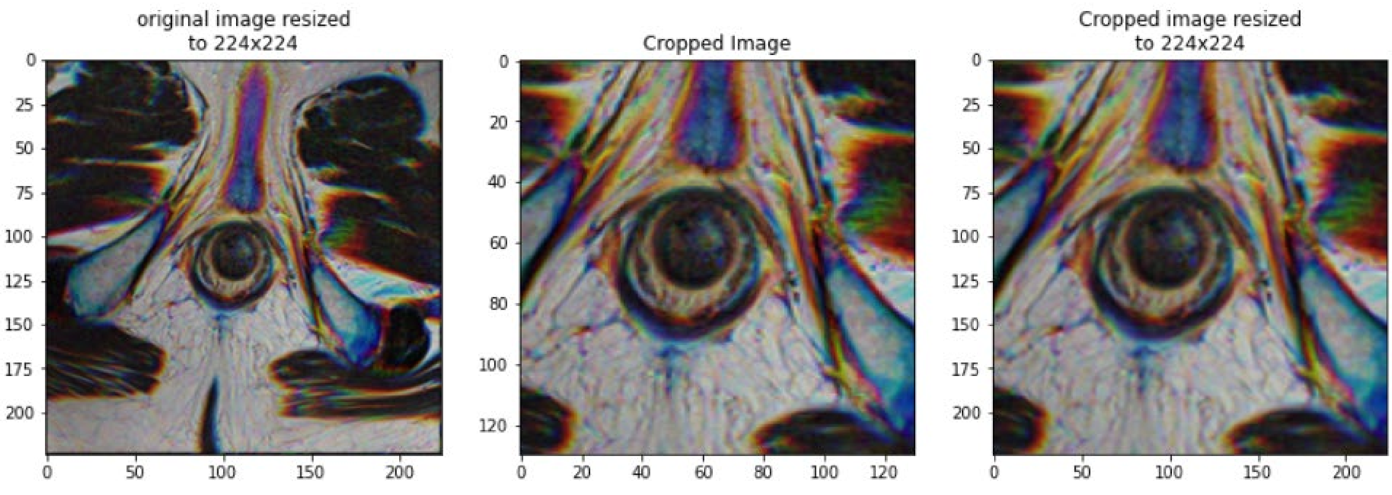


Figure 19: Cropping region of interest

Course of action tool

The course of action tool is a python-base software that allows the user to select an MRI image and predict the if the patient needs surgery or radiochemotherapy. This software uses the trained model to predict the course of action. The following image display a stage 3 MRI and its result.

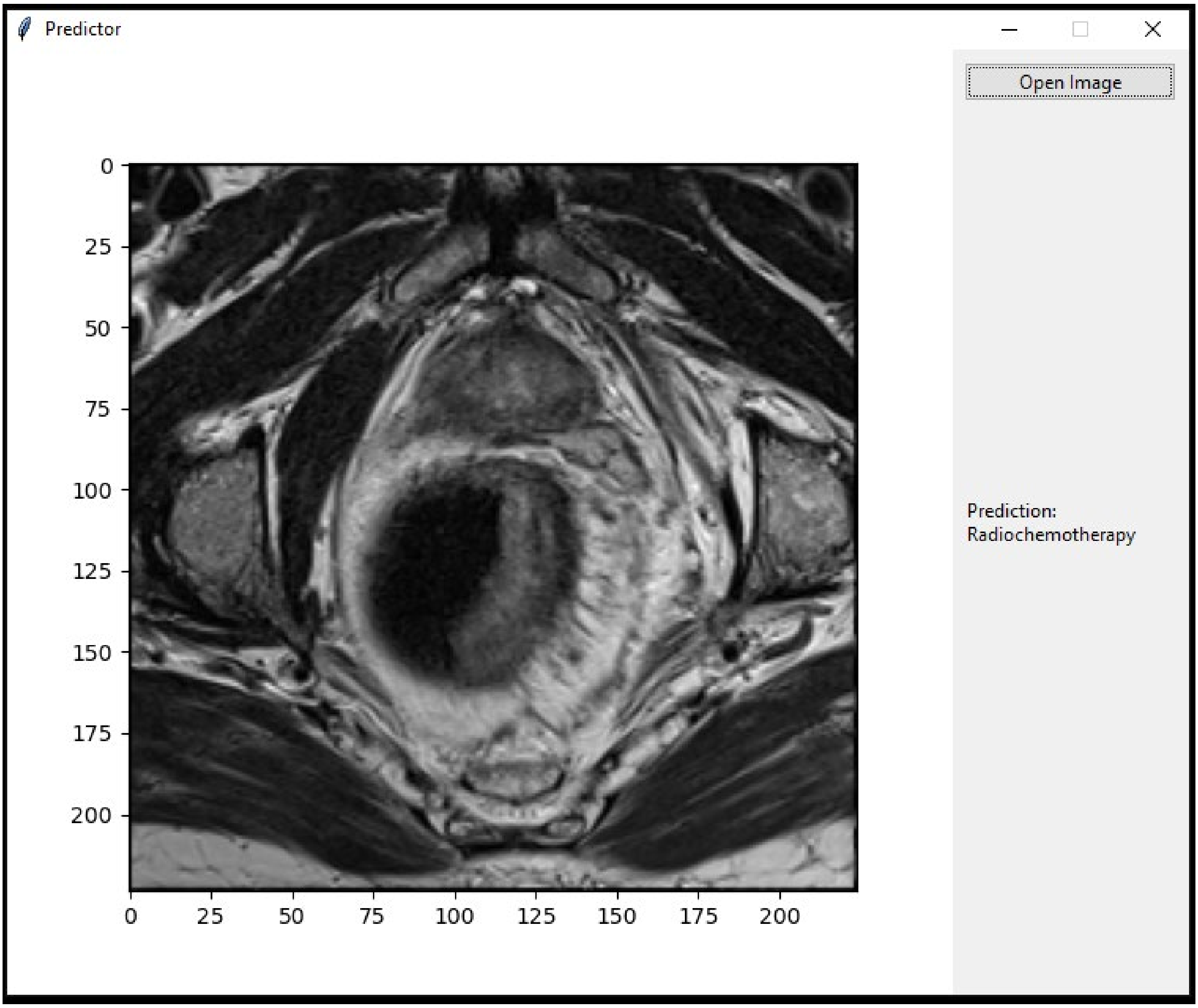


Figure 20: Course of action predictor.

Lymph node Extraction

Approach

The initial stage involved analysis of the images manually and through vision algorithms. Based on the evaluation, 2 algorithms were developed to identify the regions of the lymph node via vision techniques. Subsequently, an annotation tool is built to annotate the regions of the lymph node manually to reduce false positives in the algorithm.

Analysis

Analysis for detection of cancerous lymph nodes:

The visual method of detecting lymph nodes with cancer is detection of non-continuous appearance and disappearance of shapes in the fat region surrounding the rectum when scrolling across the 3rd dimension of the axial MRI scans. If the shape is found to be continuous, they represent blood vessels instead of lymph nodes. When looking at the T2 and DWI axial scans of the patients it was observed that the recognition of lymph nodes is easier in the DWI scans as the cancerous lymph node and rectum appear white whereas fat region is black. But in the T2 image all the regions in the tissue appeared as different shades of grey. With this analysis it was decided that DWI scans will be used with the help of computer vision techniques such as image differentiation, intensity, and density of the pixels in the image to detect cancerous lymph nodes.

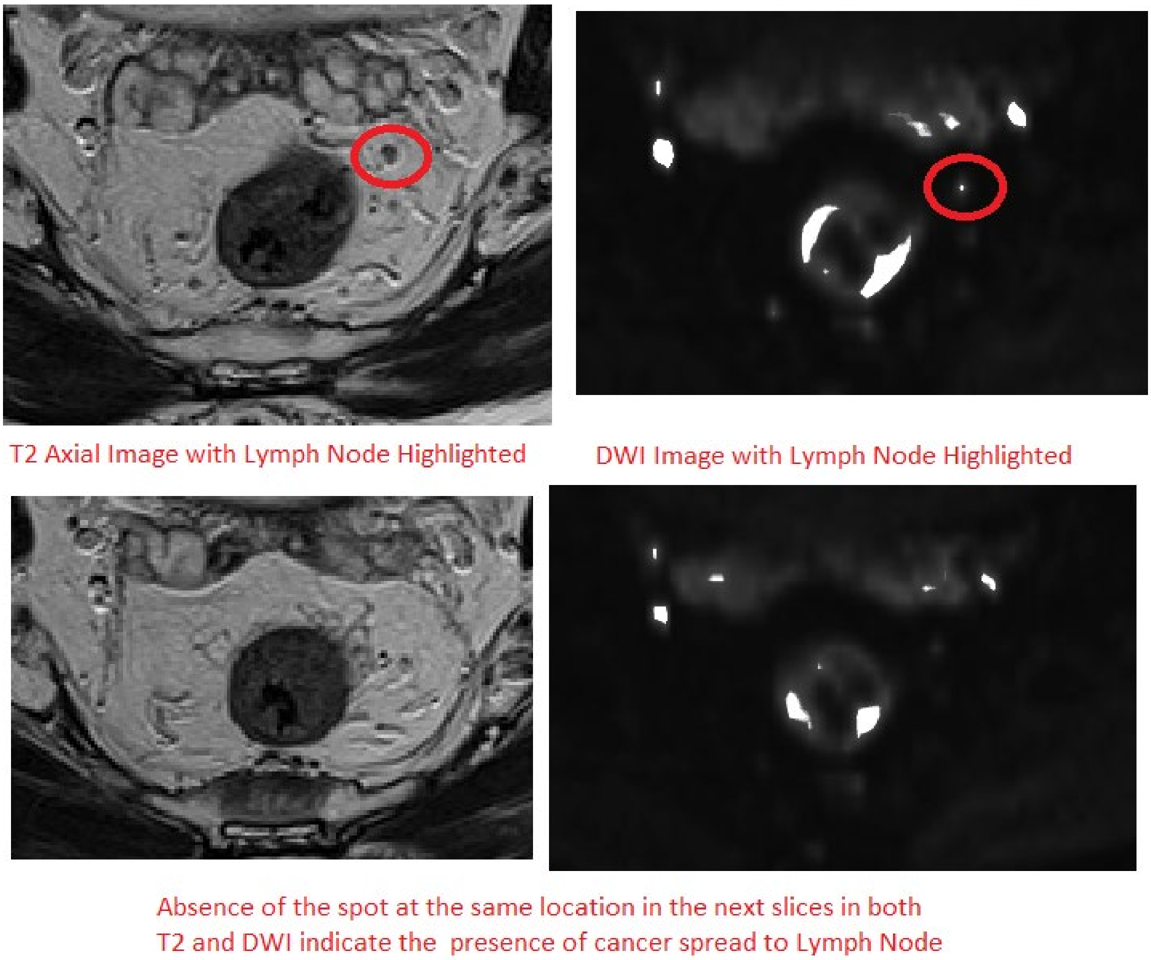


Figure 21

Algorithm for identifying Lymph node

Detecting high-pixel region by comparing 2 images

The lymph nodes are evident in a handful number of slides and identified manually from the dataset provided. Therefore, the structural similarity of the consecutive images is compared, and the circles are plotted on the high intensity pixel.

Structural Similarity

The Structural Similarity algorithm from sci-kit image package calculates the mean similarity between two images by comparing them in a sliding window pattern. The results obtained has a similarity index ranging between (0,1), with 1 being 100% identical structure. The colour intensity of the compound images is increased by performing thresholding algorithm on the compared images to detect the differences in the darker regions. From the figure, the difference between 2 images is clearly visible.

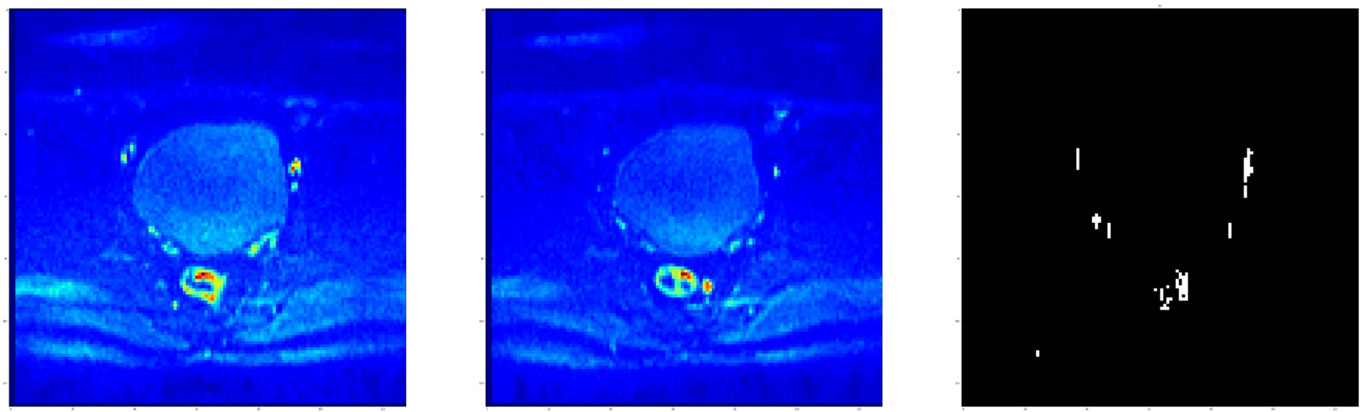


Figure 22: *Sample of Structural Similarity*

Cropping Image
With regards to the previous analysis, it is determined that the region of focus is near the rectum and the remaining area of the image is discarded. Thereby, the rectal region is cropped manually between (45, 95) on x-axis and (60, 110) on y-axis for all the images, as the lymph nodes are observed in this region on manual analysis. The figure below illustrates the cropped region.

Drawing circle
With the region cropped, the average of the location of the high pixel values are taken, and a radius of five pixel values is outlined by a circle. The figure 23 represents the high pixel values around the cropped region that are identified by the algorithm.

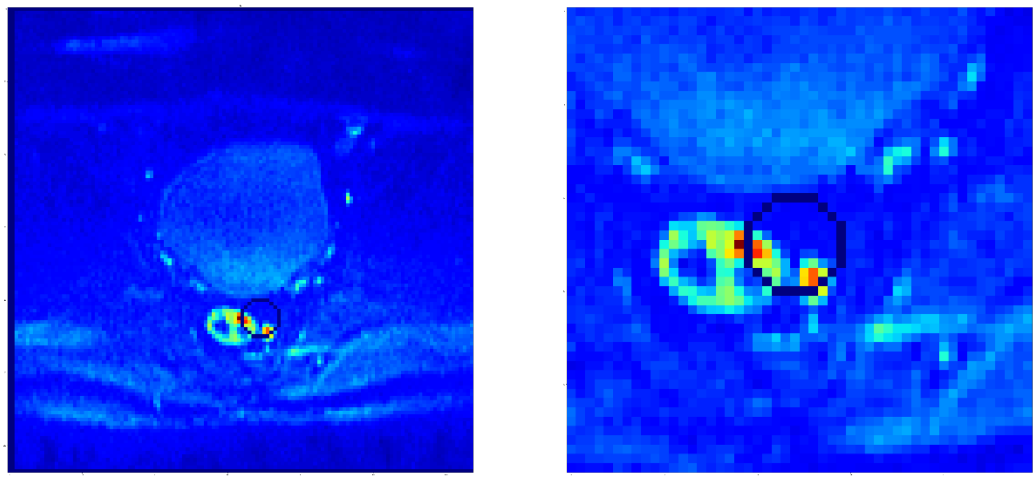


Figure 23: *Algorithm correctly identified the lymph node region.* ***Left:*** *Full Image****, Right:*** *Cropped region*

Identifying all the high-pixel region:
From the results obtained from the algorithm. It is ascertained that the high-pixel intensity regions are not lymph nodes and contained numerous false-positives as discussed in the Results and Evaluation section. The next step is to design an algorithm which identifies multiple high-intensity regions in each image, which helps to provide manual annotations on Lymph nodes. The algorithm is compiled based on the images provided by image segmentation algorithm and hence the region of focus is precise when compared to the previous algorithm.

Thresholding
Initially, the thresholding is employed on the image where the pixel value is greater than the threshold value and is modified to the highest pixel value (white). The pixel value less than the threshold value is modified to the lowest pixel (black). The resultant image after thresholding is shown in the figure.

Connected Component Analysis
Labelling the connected components is a crucial step in this algorithm. The Connected component labelling is an algorithmic application of graph-theory, is used to determine the connectivity of blob like structures in the image. Label method from Scikit-image package helps to obtain the connected components. The 3rd plot of the figure indicates that each blob like region is coloured differently emphasizing that they are labelled individually.

Masking
The labels from the previous step are copied to a new image. However, the outliers are handled while masking. As the size or shape of the lymph nodes are random and irregular, most of the blob's structures between 2-pixel length and 200-pixel length is considered. From the figure, it can be seen that some of the small blobs were eliminated from the image.

Contour detection & Plot Circle
Final step is identifying the contours and draw circles around them. The contours are identified using *opencv's findcontour* method and sorted with the help of image utilities (imutils) package. Eventually, for each of the contours, the minimum enclosing circle which represents the high-intensity region is identified. Finally, the circles are drawn on the original image as depicted in the figure.

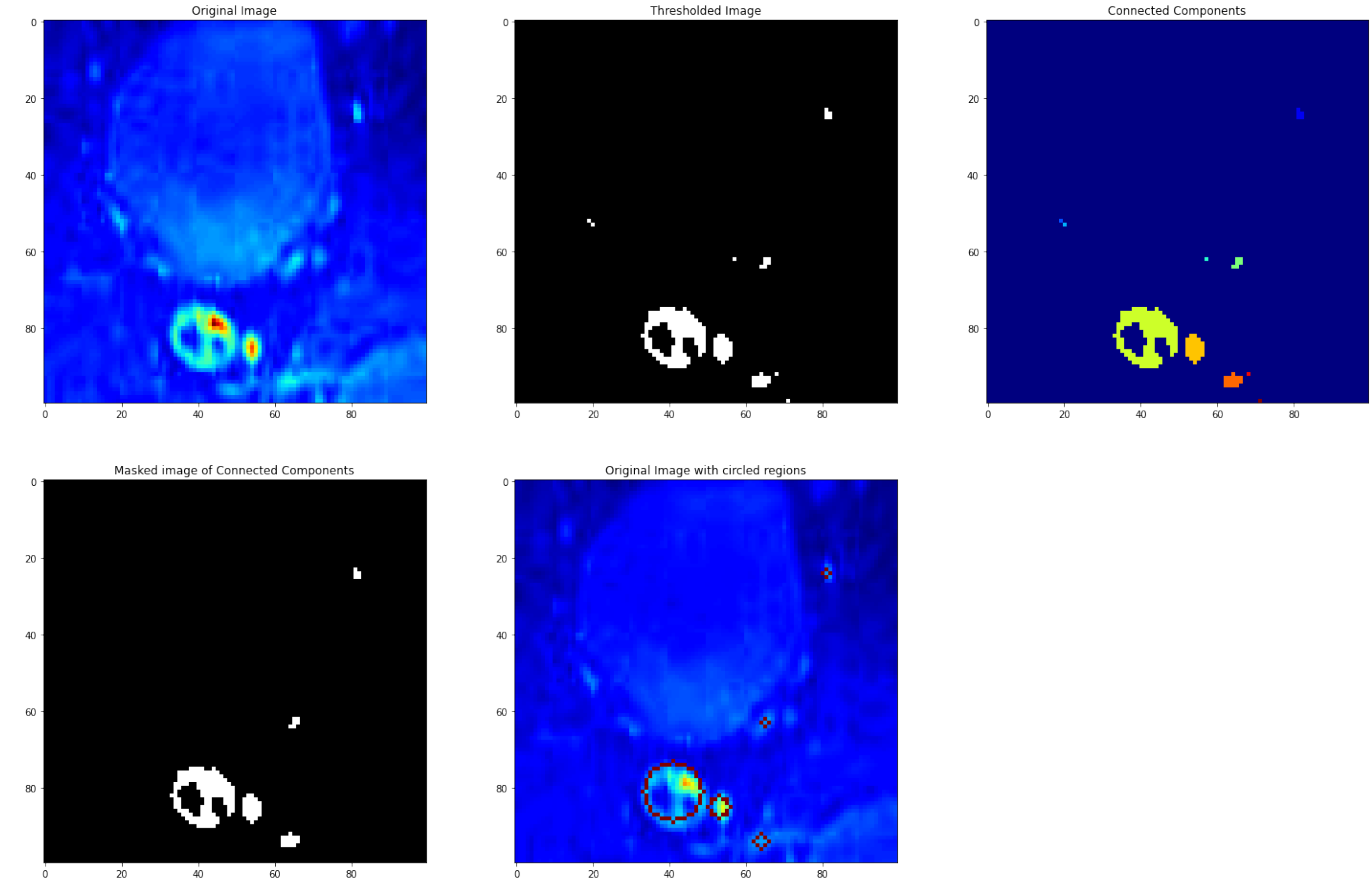


Figure 24: *Process of identifying the regions of lymph node*

Building an Annotation Tool:

The lymph node region identification algorithm is able to clearly circle out all the regions similar to lymph node and the next step is to manually annotate the images. As the data is confidential, it is advised to avoid using online platforms to perform the annotation and hence the team has developed a tool which is able to annotate the images on a single click.

The tool is simple and powerful which is developed using the TKinter python package. Initially, the folder that encompasses the images of lymph node region is selected by the user. Once the image is plotted on the window, the next step is to click on the region to annotate. On selecting the region, the location of selection is automatically updated on the x & y position boxes which helps the user to validate their selection. Then the user can save their annotation after selecting the choice from the radio buttons. The user can move to the next image by clicking on the next slide button. Another advantage is that the application allows the user to annotate multiple regions in a single image. Once all the images are annotated and when the user clicks on Exit, the application will generate a CSV file comprised of the annotated regions, path of the file and label of the annotation.

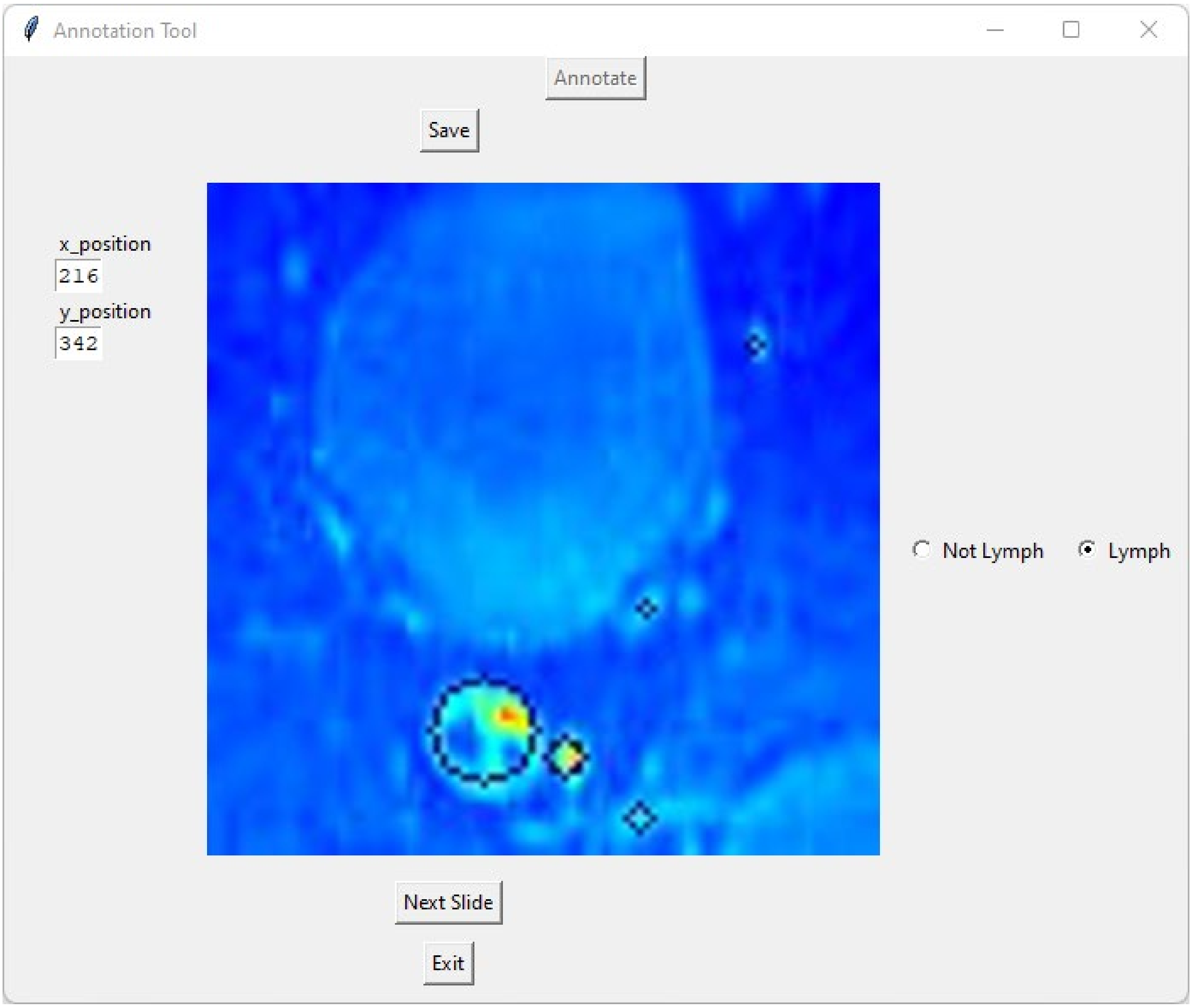


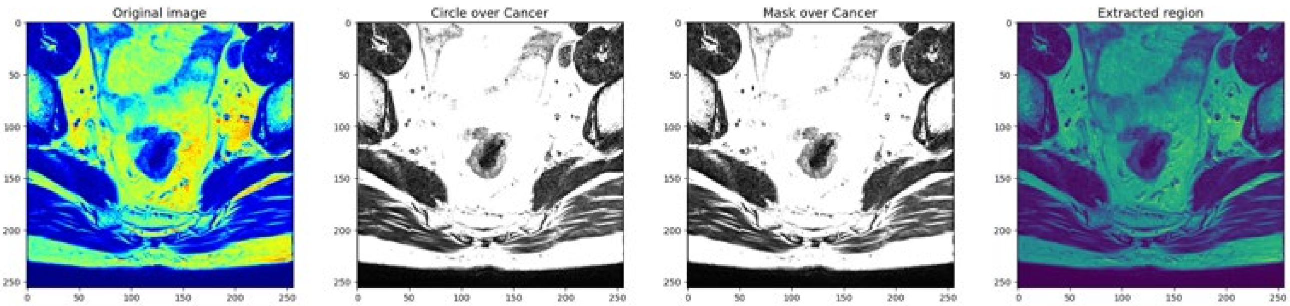
Figure 25: *Annotation tool, annotate window.*

Results, Evaluation & Analysis

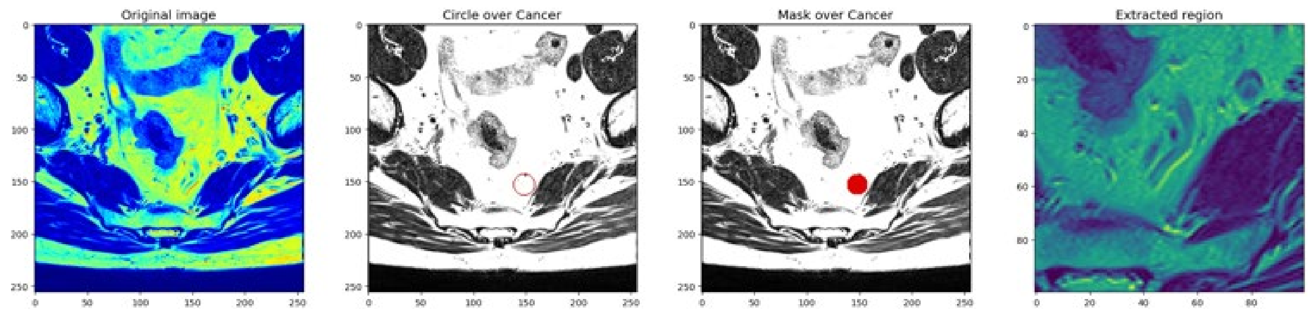
Challenges in the segmentation

After segmenting the rectum region from the images to create a new refined dataset, we observed that the algorithm is not able to find rectum in all the MRI images and the main reasons for that were:

1. Not all rectum regions were circular. This misleads the algorithm, and it investigates other regions. However, after applying thresholding, all the regions were ruled out (figure 26 (a)).
2. In some cases, the surrounding regions of the rectum were also circular with an average pixel value inside the threshold range which causes the algorithm to mark those regions as rectum.



(a) *The segmentation algorithm is not able to find rectum in the MRI, the rectum is not circular*



(b) *The algorithm marks a wrong location as rectum*
Figure 26: *Challenges in segmentation*

Course of action predictor

The predictor performed well on training data. However, while testing on unseen cases the model accuracy drops in comparison to the training set. This is call overfitting and it happens when the model is too complex or when there is not enough data to generalise appropriately. Loss and recall metrics were chosen to evaluate the model trained during 30 episodes (epochs). A loss near to 0 mean less errors while predicting. The recall metric penalises false negatives. For example, "if a sick patient (Actual Positive) goes through the test and predicted as not sick (Predicted Negative). The cost associated with False Negative will be extremely high if the sickness is contagious" [15]. A recall accuracy near to 1 means better predictions. The following graph depicts the mentioned metrics, in a continuous line represents the training data, the dashed line represents the validation data.

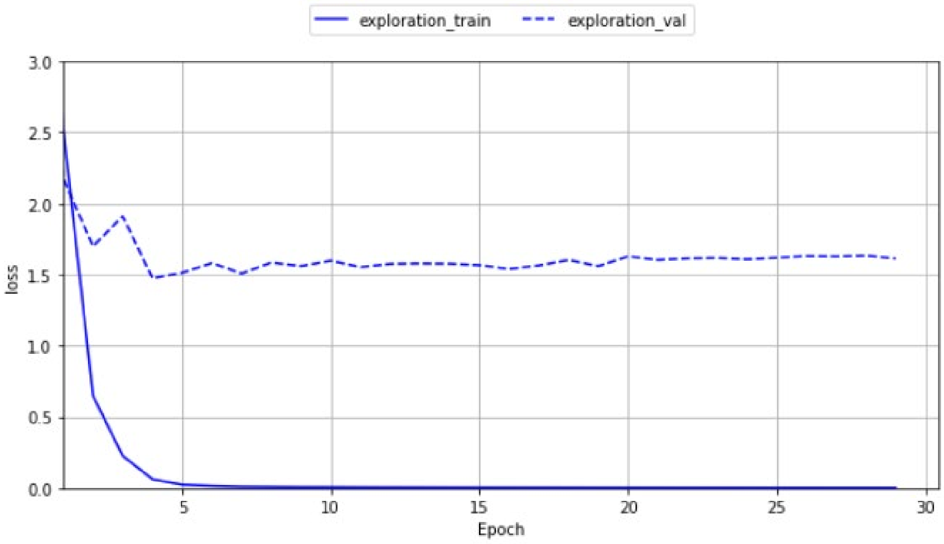


Figure 27: *Loss after model evaluation*

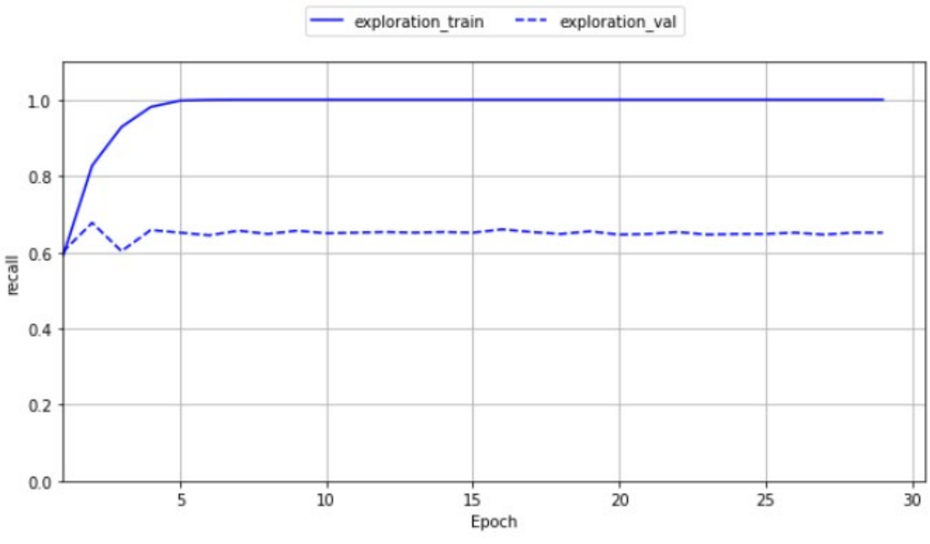


Figure 28: *Recall after model evaluation*

Lymph node Extraction:

The algorithm to identify high-intensity image by comparing 2 images was able to identify the lymph node region. However, the algorithm generated lots of false positive cases. As explained earlier, the lymph nodes are not available on all the slides, also the size and shape are irregular and random. From this algorithm it is also identified that pixel intensity of the lymph node is also random and there are lots of regions as same colour as the lymph node. consequently, the algorithm generated lots of false positive cases.

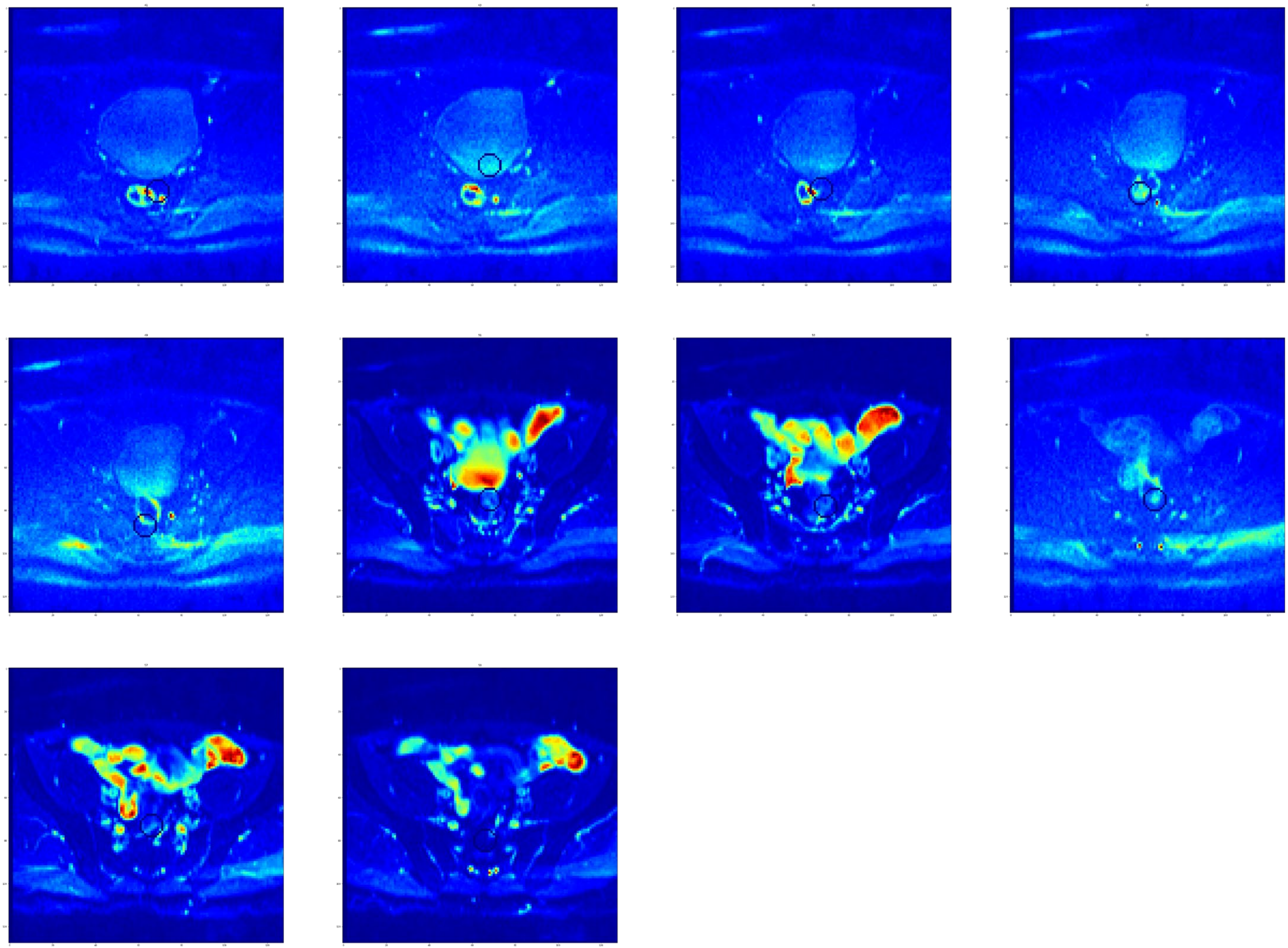


Figure 29: *Results of initial algorithm to detect lymph node region.*

In order to identify the cancerous lymph regions by reducing the false positive cases, an algorithm to locate multiple spots in the image is developed. This algorithm is able to clearly identify all the regions which is exactly same as the lymph node region, the figure shows some of the examples.

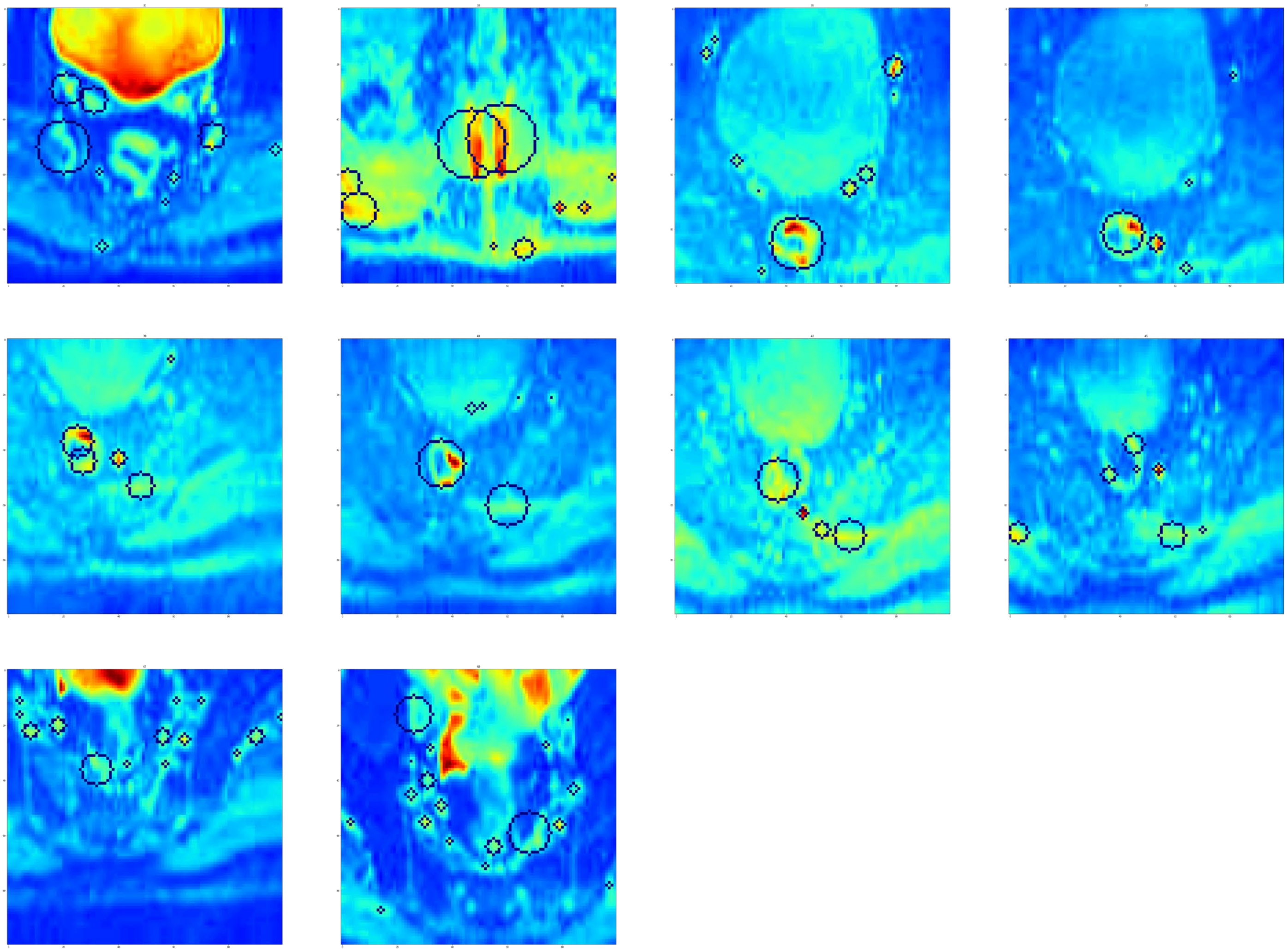


***Figure 30:**Results of the algorithm to detect similar regions of lymph node. The 4th slide contains the lymph node and the algorithm was able to identify it.*

Conclusion

The project began with our limited knowledge in medical domain and beginner knowledge in deep learning AI techniques. Over the course of the project, we developed the skillset to understand and tackle the challenges involved in an industrial level project particularly in medical domain. From collection of data to building final deliverables in line with expectation of the clients and course co-ordinators we learned to convey our progress, generate production level deliverables and software engineering lifecycle involved in an Artificial Intelligence product development process. We utilised the expertise of our academic supervisor in the domain of deep learning in medical field to narrow down our research and converting it to practical application in the given limited time frame and data provided by the industrial partner. At the end of the project, we delivered the software containing three major software components which can be used by medical professionals to help segment and the MRI scans, Annotate the scan images with recognition of lymph nodes and recognize the stage of the rectal cancer.

Future works

For the lymph node extraction part, after the manual annotations are done on the segmented images, a deep learning model is built to identify whether the model is able to learn the region of interest. According to the journal [24], the masked R-CNN model with annotated DWI images will be able to localize the lymph node with better accuracy. The future works would be to build and compile deep learning models on the annotated images.

Regarding the course of action, it is crucial to gather more data of the segmented region of interest (the rectum). This data must contain the tumour and its stage, slices that does not comply with these requirements should not be used to train the model. By having more samples, the generalisation gap will narrow down, providing a better model, thus, better predictions. The course of action tool can read new models by putting them within the Models folder of the delivered software. A readme file with instructions will be provided in the software documentation.

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Appendix

Roles

Amogh Varsh Nagaraja

- Role: Machine learning practitioner, coordinator. In charge of the course of Lymph node extraction.
- Responsibilities: Initial report and group work preparation, Collecting the data (CD), Transferring data to the RMIT server, Data analysis of patient scan details, Initial approach of lymphnode classification, Lymph node extraction, Stakeholder presentation and Final presentation.

Juan Sebastian Valencia Sanchez.

- Role: Machine learning practitioner, expositor, coordinator. In charge of the course of action predictor.
- Responsibilities: Initial report and group work preparation, Dataset creation reading DICOM data, Initial approach of stage classification, Course of action predictor, Activator pitch presentation, Activator final showcase, Stakeholder presentation and Final presentation.

Karthi Narendrababu Geetha

- Role: Machine learning practitioner and expositor. Working on Lymph node extraction.
- Responsibilities: Initial report and group work preparation, Collecting the data (CD), Transferring data to the RMIT server, Dataset creation reading DICOM data, Initial approach of lymphnode classification, Lymph node extraction, Activator pitch presentation, Activator final showcase, Stakeholder presentation and Final presentation.

Prabhat Kumar Singh

- Role: Machine learning practitioner expositor. In charge of the rectum segmentation.
- Responsibilities: Initial report and group work preparation, Collecting the data (CD), Transferring data to the RMIT server, Initial approach of stage classification, Rectum Segmentation, Activator final showcase, Stakeholder presentation and Final presentation.

Responsibilities description

Initial report and group work preparation: Project initial plan showing and agile approach to the problem by sprints of 1 week

Collecting the data (CD): Visit the stakeholder and claim the CDs with the data.

Transferring and organising data to the RMIT server: Manually copy and transfer the data of 150+ CDs into the RMIT server. The team only had 2 CD readers since such hardware is no longer embedded in current laptops/desktops posing a difficult start of the project.

Dataset creation reading DICOM data: Investigate and create a script that reads the DICOM format and extract into csv files the following data: stage of the cancer, number of lymph nodes affected, type of image, location of the image, quantity of slices per patient, and image dimensions.

Initial approach of stage and lymph node classification: First approach to stage cancer and lymph node detection, the team applied Resnet as the convolutional neural network in charge of classify the cancer stages, determine course of action and presence of lymph nodes. Nevertheless, the results demonstrated low generalisation on unseen data what lead a change of the scope to include the rectum segmentation tool.

Rectum Segmentation: This deliverable is a python script and a user-interface. The script generates segmented rectum region for the entire dataset containing DICOM files for both f2 160 FOV and DWI images. The user-interface is for browsing through the DICOM dataset, viewing and correcting the segmentation results.

Course of action predictor: This deliverable is a python script-based user interface that uses a trained Deep Learning model to predict if the patient should proceed directly with surgery or if radiochemotherapy is required as first measure. The user interface allows the user to select a DICOM image of the rectum display its prediction.

Lymph node extraction: This deliverable is a python script-based user interface that uses the algorithm for identifying the lymph node regions to generate new set of images which then be used to annotate the exact lymph node regions.

Activator pitch presentation: Presentation video prior final showcase inviting the community to join the final showcase.

Activator final showcase: Presentation along other activator projects and enterprise guests, displaying the work done, challenges and next steps.

Stakeholder presentation: Showing the deliverables capabilities to the St Vincent's Hospital representatives, the completed project as a software product and recommendations to evolve and improve future versions.

Final presentation: Showing the deliverables capabilities to the course coordinator, the completed project as a software product and recommendations to evolve and improve future versions.

Virtual collaboration

The team used Microsoft Teams, Slack, One Drive and Google Drive for collaboration. In general, there were between 2 and 3 meetings per week, an internal follow-up with just the team members, a consultation with the supervisor, and expert consultation with the client. The last one is subject to client's availability.

During the extraction, Karthi, Prabhat and Amogh worked together to transfer the data from the CDs to the RMIT server. As soon as the data was on the server Karthi and Juan created the dataset, input of the following tasks. Then, the team formed 2 sub-groups, Karthi and Amogh did work on the Lymph nodes classification and Prabhat and Juan worked on the cancer stage classification task. As a result of the first approach the rectum segmentation tool was needed. Therefore, Prabhat took responsibility of this whilst Juan continued working on the course of action predictor (stage classification)

As an estimate, Karthi and Amogh did work together an 80% of the time, leaving the remaining 20% for miscellaneous contributions like report writing, video presentations, and slides preparation. Prabhat and Juan did work together approximately a 40% of the time given the unplanned segmentation tool. Then the remaining 60% for Juan and Prabhat was distributed 40% for individual progress (course of action predictor and segmentation tool respectively) and 20% for report contributions, video and speech preparation, and presentation slides.

On average each member invested 17 hours per week on the project in addition to weekly presentation to client, RMIT impact agency and discussion of direction and progress with supervisor. The following table shows the group and individual approximates per week.

	Hours of group work	Hours of individual work	Total
Amogh	14	3	17
Karthi	14	3	17
Juan	10	7	17
Prabhat	10	7	17

Self-reflection (Individualised)

The project is started with zero knowledge on the medical images and also on the biological parts of the human body.

Knowledge from the Radiologist

With the expertise of the Radiologist, the following are learnt,

- Understanding the concepts behind the MRI images,
- Understanding the concepts behind the Rectal Cancer,
- How to obtain information from the MRI images,
- How to locate and stage cancerous cell in the rectal region,
- How to locate the cancerous Lymph nodes.

Knowledge from Supervisor

From the supervisor, the following outcomes were learnt,

- How to kick-start a deep learning project.
- How to accept the real time data and make use of it.
- How to assign tasks to the teammate.
- Ways of solving a deep learning problem.
- How to provide deliverable to the client.

Self-Learning

- Improved knowledge on staging and localization of the rectal cancers and the lymph nodes.
- Expertise on reading and parsing the Dicom MRI images in python.
- While working on the lymph node analysis, the expertise on the computer vision algorithms are obtained. Plethora of of the computer vision techniques were used as part of the analysis.
- Understanding of how unsupervised learning techniques are performed in the deep learning problem.

Research might've been completed

Initially, after the development of custom data loader for the model, an auto-encoder model on the given dataset was to be developed. In addition to developing another deep learning model to detect the stage of the cancer with aid of weights from the auto-encoder model. The model was not implemented because the client requested to work on the lymph node extraction part.

Achievements:

- Successfully cleaned the data and made it ready for use.
- Identified the flaws in the data and prepared the data accordingly.
- Built tools to improve the quality of the data.
- Identified that the deep learning model will not provide better accuracy with the given data.

Mistakes & External factors

Even though, there were lots of learning outcomes, some of the mistakes can be avoided, such as

- Even though some of the insights were gathered from the algorithm for identifying single high intensity pixel region, it might have been avoided, as it didn't make much sense at the end.

External factors that affected the improvement of the project, such as

- Since the project started at the end of 4th week and hence 8 weeks' time was not sufficient.
- Also the Covid 19 restrictions affected the collaborations between the teammates, client and the supervisor.
- The data received in a cd format and it took 2 weeks to digitalize them once by one.