Renal Segmentation in Dicom CT Images

A feasibility study for predicting different types of renal tumor

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Overview :

In this project, we explored some segmentation techniques to extract kidney from the CT scans in dicom files in order to train neural network with regions of interest. First preprocessing techniques were applied to the dicom files. Then, the clipping of intensity values of pixels were done to separate the interested kidney region from other unwanted regions in the scans. Morphological operations for fine coarse kidney segmentation were applied which was used as a template to extract the desired region in all of the slices for each patient. Furthermore, filtering technique was also used to remove noise from the images.

1. Introduction :

Deep learning-based medical image analysis and prediction of cancers has been effectively used in the medical field; aiding radiologists and physicians in quick efficient decision-making process and treatment of patients. The goal of this project is to segment the kidney region and investigate the feasibility of learning the segmented renal images using neural network models in order to predict cancer types.

Image segmentation and processing is vital in the medical field specially to diagnose brain, lung, cancer, kidney tumors and much more. There are various methods proposed in literature to perform automatic kidney segmentation based on imaging features, clustering approach, region growing methods, deformable models and deep learning algorithms such as UNET. However , as our dataset contained slices of the entire abdominal region and were not annotated, deep learning models were not possible to apply for segmentation. So, a region growing approach based on morphological operation was chosen to segment the kidney.

2. Method:

2.1. Data:

Axial computed tomography (CT) scans from 113 kidney cancer patients were used for this project. Upon data exploration, 6 different types of renal cancer types were observed with 12% out of total cases being non-malign cancer cases. The data set was highly unbalanced and likewise while observing cases for each cancer type . There were also variations in the number of slices for each patient, brightness and positions of scans. Some of the scans can be seen in figure 1 below. Owing to these variations, preprocessing of the slices were done using computer vision techniques to maintain uniformity across all cases .

2.2 Image Preprocessing :

The dataset had inhomogenous voxel pixel spacing in each of cases, therefore some image preprocessing had to be done so that convolutional neural networks would compare and interpret images efficiently. So, the first step of preprocessing was to resample all cases to a common voxel spacing. There was trade off between voxel spacing and detailed information. Increase in resampling of the slices would cause some information to be lost. Here, we resampled all cases to a common voxel spacing of *1 x 1 x 1 mm* using interpolation.

As CT images are quantitative, a particular organ will contain same intensity values in hounsfield units. This property of the ct images can be used to form a window by clipping the intensities values related to the interested organ of study. Here, we had a window of range -30 to 300 so that it would also include intensity values related to soft tissues of tumors.

Images were then normalized to pixel values between 0 and 255 (unsigned 8-bit integer format). Histogram equalization and Otsu's thresholding were performed to produce a binary mask. Median and mean filters, with 9 x 9 and 15 x 15 sized kernels, respectively, were convolved with the binary mask to remove noise. A flood-fill algorithm was used to fill holes in the foreground, and then morphological operation was performed to remove smaller foreground objects (specifically aimed at removing the patient table). This binary mask was then multiplied with the image to remove the table artefact and other sources of noise. Finally, images were down-sized to 128x 128 pixels. Preprocessed images are shown in the second row of Fig. 2.

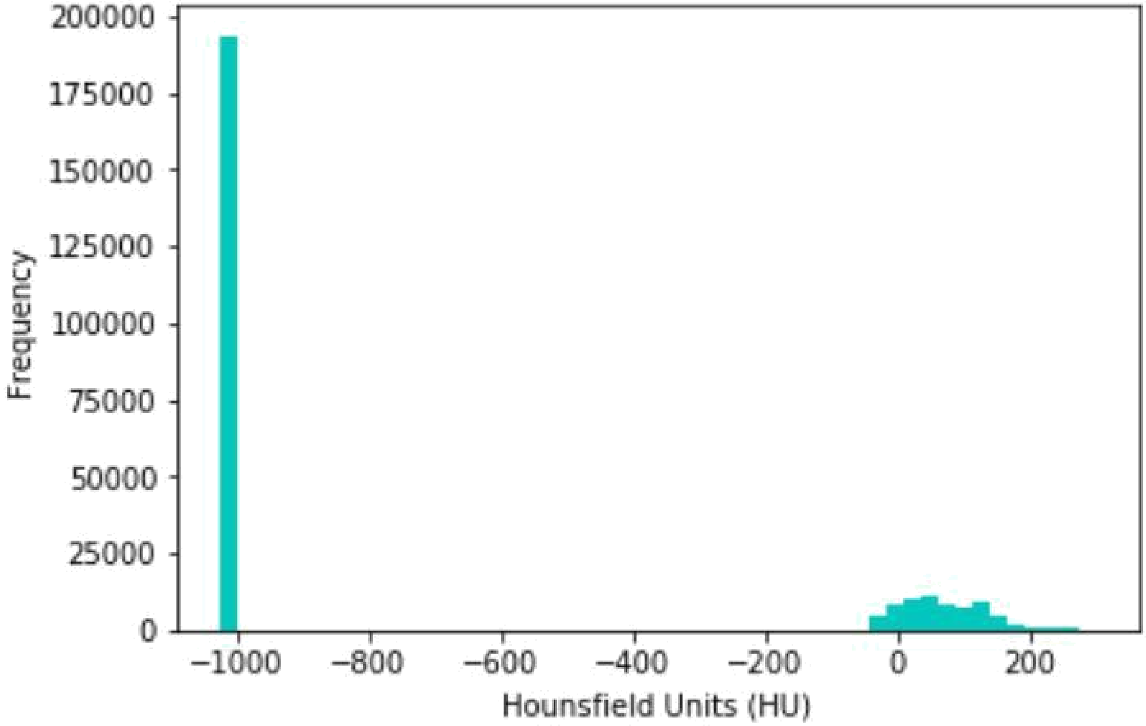

Fig:1 Histogram of pixel values in Hounsfield units(HU) after clipping

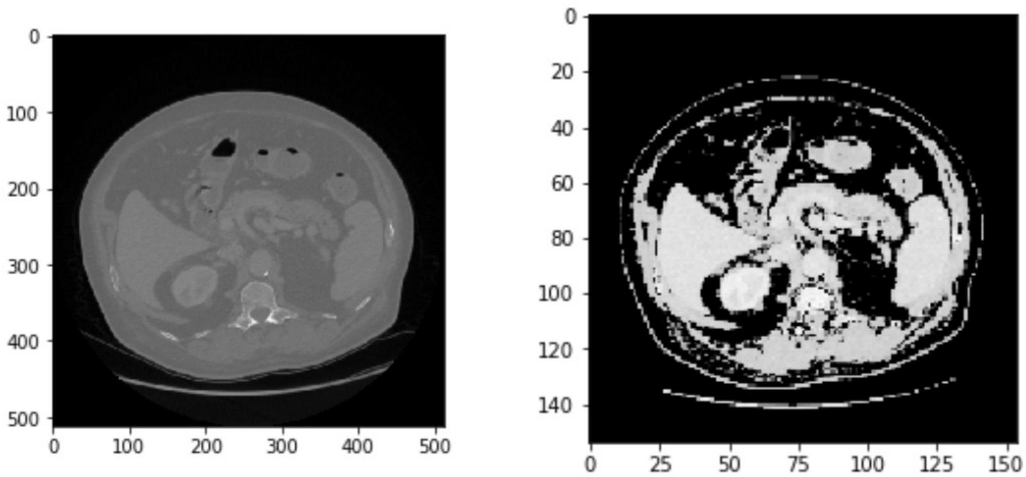

Fig 2: Before and after applying preprocessing techniques.

2.3. Workflow architecture for segmentation :

For obtaining the final segmented image, the preprocessed image was taken and then the morphological algorithm with thresholding was applied which involved erosion followed by dilation. Erosion will remove some bright pixels from the edge. The dilation will preserve foreground regions which are similar to the structuring element and remove the unsimilar ones.

The workflow steps in obtaining the segmented image included taking the abdominal CT scans as input , preprocessing and clipping pixel values related to the uninterested region. Furthermore, steps involved resizing of the image, converting into grayscale, noise filtering, intensity equalization techniques for a uniform distribution of intensity in the image. Finally, thresholding was applied to separate the desired kidney region and after which morphological operations are applied for fine segmentation.

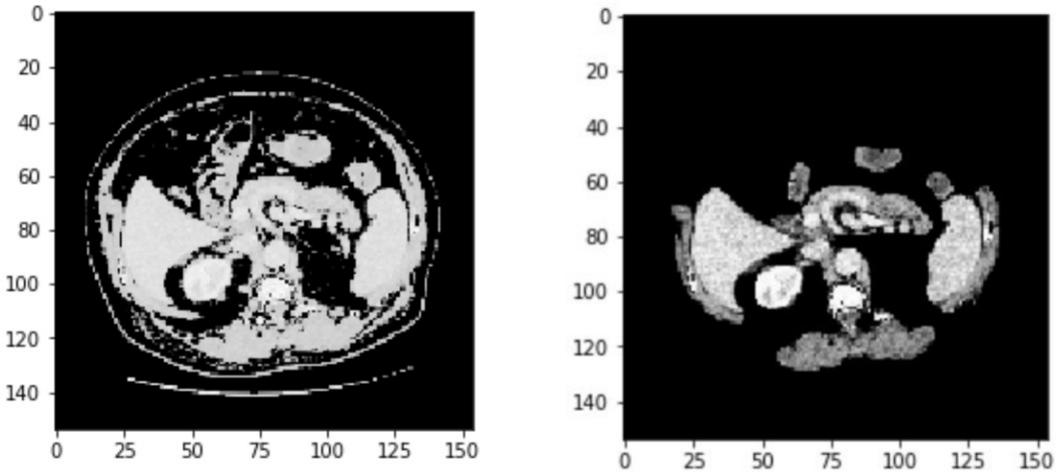

Fig 3: Before and after applying segmentation.

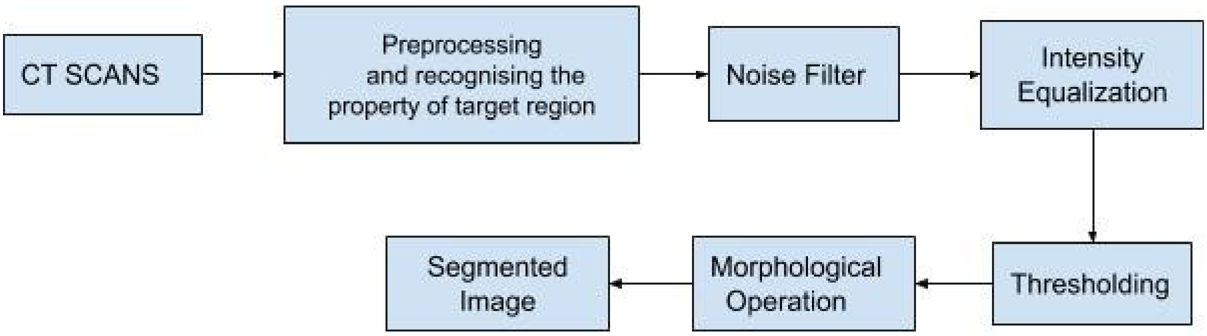

Fig 4: Workflow architecture showing the fundamental steps .

3. Discussion and Suggestions:

As the provided dataset was not annotated, the segmentation and extraction of the kidney region became vital in order to obtain good training results for learning algorithms. Moreover, the CT images contained an overall view of the abdomen in 3D volume and it failed to provide an accurate view of the kidney region. So, in order to locate the exact position and clean the CT images; various image processing techniques such as filtering, thresholding, morphological operations e.t.c were applied .

During this first phase of the project, the work done helps us to conclude that morphological processing techniques are significant when the dataset is not annotated by radiologists and lacks images just related with kidney regions. Manipulating the kernel size in the morphological operation, we will be able to enlarge or shrink the region of interest in the image.

Some of the suggestions that can be incorporated in the next phase of the project:

1. Observe the result by training the 2D neural network with the preprocessed image dataset after the first phase.
2. For improving the training dataset, properly annotated equal number of CT images for each case in relation to the region of interest(ROI) can be requested from the source. This will enable us to perform focus training on a 3D neural network to yield better results.
3. With the annotated CT images, U-NET could be used for segmentation of tumor and kidney.
4. The current dataset also did not contain enough observations under different types of renal cancer types. Increasing these observations in the dataset could enable training algorithms for detecting and predicting specific renal cancer types in future work .

References:

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