Liver Segmentation Using Computer Vision

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Abstract - There has been a fast pace in the practice of comparing image analysis algorithms based on enormous challenges. There have been numerous investigations into the segmentation of medical images. Nevertheless, most challenges are structured in a way that centers on specific clinical tasks relevant to the challenge. We intended to investigate the hypothesis that if a method is capable of handling multiple tasks, it will also be capable of handling previously unseen tasks better. According to this study, state-of-the-art image segmentation algorithms generalize well when retrained on unseen tasks. This suggests that the algorithms are effective at distinguishing between different objects in a photo. Furthermore, consistent algorithmic performance across multiple tasks is a strong surrogate of an effective algorithm.

Nomenclature

(Nomenclature entries should have the units identified)

= Digital Imaging and Communications in Medicine

= hepatitis C vius

= Computed Tomography

= Liver Tumor Segmentation

= Neuroimaging Informatics Technology Initiative

= Radiotherapy Structure Set

= Hounsfield unit

= Rectified Linear Unit

I. INTRODUCTION

The second main cause of death is due to liver cancer. The five-year survival rate for all cancers is 10 percent. As part of the preprocessing process, after the liver was isolated from the scan by using HU windowing, the radiotherapy structure set (RTSTRUCT) DICOM file was used to create the masks for the liver and tumor, and as part of this process, the images were converted to PNG format. As part of the RTSTRUCT file, the physician was required to manually label the ground truth contours for the liver and tumor in order to prepare the RTSTRUCT file. A U-Net is used in the first network, to segment the liver, and a U-Net is used in the second network, to segment the tumor based on the liver segments produced by the first network

The five-year survival rate for all cancers is 10 percent, according to the most recent report. This number varies depending on the stage of the cancer at the time of diagnosis, but it's still an optimistic statistic. In fact, the rates are even better for some cancers: 20 percent for early-stage cancer and 50 percent for those in remission. However, no one is guaranteed a five-year survival rate, and it's important to know what to expect depending on your diagnosis.

II. RELATED WORK

Though the segmentation done by experts is reliable, this requires lots of time and effort. In addition, such experts who can make accurate and fine segmentation are very few and are limited access to the people of developing countries where the issue of liver cancer is more prominent. These issues create a need for a computer-aided or computer-assisted system that utilizes a better, more accurate, and effective algorithm for segmentation, to determine tumor size, shape, and location.

There is a need for a fully automatic segmentation technique that can segment both the liver and tumor in a single run. Such a technique would be very helpful in assisting doctors or radiologists without user interference, reducing reading time, increasing detection sensitivity, and improving diagnosis accuracy and early detection of tumors. These methods could also be used after proper testing in places where there are no experts in liver imaging.

Research in recent years has been towards developing a fully automatic method that can make accurate and timely predictions of liver tumors, saving a lot of efforts. The benefit of a fully automated method is that it can evolve over time through its output and integration of ranging conditions and inputs. A large number of researches that have emerged lately support this proposition.

III. METHODS

The procedure of proposed system starts with data collection, pre-processing, feature extraction, training and testing with different machine learning and deep learning algorithm and lastly evaluation of models by several measuring parameters.

A. DataSet

To create a ML model, the first process is to select the data and choose the best dataset. The data must be clean(without null values) and error-free(data should be relevent to the label) to get the best results. In this case, we have chosen the Liver Tumor Segmentation data from Kaggle.

This dataset was extracted from LiTS organized in conjunction with ISBI 2017 and MICCAI 2017. The CT scan data and various segmentations are available at various clinical sites. The dataset is related to liver CT scans of multiple patients to find the tumor in the organ.

B. Data Analysis

After downloading the dataset of liver CT scans, you will find that the data is in the form of '.nii' files. These files mostly belong to the NIfTI-1 data format, which was created by the Neuroimaging Informatics Technology Initiative. NIfTI-1 is inherited from the ANALYZE 7.5 file format.The dataset contains data of 120 patients in '.nii' format. This includes liver and tumor data of the patients. The dataset is divided into two directories: "volumes" and "segmentation". The "volumes" directory contains all the CT scans of the liver of the patient. The "segmentation" directory contains the liver tumor data.

C. Matching the data

The volume data and segment data are in different folders so if we need to access both the data we need to match the data based on addresses of the data. We are overlapping the volume and segment data over each other using the masking layers. So, from the volume it will take the CT scans images and apply the mask i.e., the segmentation on the volume CT scan. Then we are reading the .nii files which are not completely in the image form and returning the pixel array which is in the matrix of (512,512,75).

D. Pre-processing

Performing pre-processing on the .nii file that is NIfTI file format. We are also using dicom.window for the namespace where every organ can be displayed based on the location value or array values. We defined liver = (150,30) array/index of its position in the dicom window. We are plotting the labels on the volumes and segments data, then we are performing pre-processing on the functions.

Some function we are using:

1) freqhist-bins: split the range of pixels into group.
2) hist-scale: it manages the value of freqhist-bins that are in between 0 and 1.
3) save-jpg: saving the images and data in jpg file format.

Generating the jpg file for the training part, we are taking half of the data i.e. .nii file for the training. For 131 .niifiles there are 67072 slices, it takes volume data and segments data then merges data and converts it into .jpg files.

E. Model Training

The next part is training the model. We are taking 3 main parameters for training data background, liver, tumor each of them labeled as, background: 0, liver: 1, tumor: 2. We are also using df-datablock for initializing the data for pre-processing and dataloader to load the training data, dataloader is a class of fastai. Then we compute non-background accuracy for multiclass segmentation if required in the training.

Visually, the liver and tumor segmentation match the ground truths decently. It looks like the model has a difficulty segmenting on the edges. Moreover, the liver segmentations seem to be more accurate than the tumor segmentations. The images that are generated, consist of the raw data along with the masked images representing the liver. The liver is detected using the masked layer, coloured differently than the raw image. It will detect liver and highlight them in red colour and ignore the other where there is no liver detected.

F. U-net

The convolutional network consists of a contracting path and an expansion path; the contracting path follows a typical architecture for convolutional networks, but the expansion path is different.A down sample is formed by successively applying two 3x3 convolutions, followed by a ReLu and a 2x2 max pooling operation with stride, followed by rendering the down sample with the final application of two 3x3 convolutions.

U-Net is a deep learning semantic segmentation technique used for medical image segmentation. It was one of the earliest deep learning segmentation models, and the U-Net architecture is also used in many other operations.

U-Net is able to do image localisation by predicting the image pixel by pixel. When excessive data augmentation techniques are used, the network has enough strength to perform good predictions on even a few data sets by using excessive data augmentation techniques. Since the input and output are the same size, in order for it to work effectively, it is necessary to do a classification on every pixel of the image in order to localise and distinguish the borders since the input and output are the same size.

G. Testing

We are performing a similar process for the testing part, taking the data and generating the output without the help of segmentation or mask. It means the model has learned from the previous results and given the result. After testing is performed it predicts the result that if the tumor is present in the CT images of the patient or not, if the tumor is present, it will show the tumor in the form of yellow dots.

IV. IMPLEMENTATION

Combining the data which are in the form of segments and volume. For every segment there is a particular volume the same as for every volume there is a segment, so we are assigning each volume for each segment.

Pre-processing is performed after combining the data to optimize the data for further process. After pre-processing the data is converted into images, or in other words.nii files into .jpg for better accuracy and result and also for displaying the result.

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V. RESULT

Detecting liver on the original image and applying mask or segmentation on the original CT image to generate liver and mask image. Applying U-Net architecture on the train data to obtain the best accuracy and result, we got the average accuracy of 99 percent and with very minimal error rate and loss.

After training the data on the U-Net model we obtain the best accuracy as shown in the fig 8 above. The train loss and valid loss is very minimal which is a good sight as it will increase accuracy and give the best optimal result every time. Also, the time taken is minimal as compared to other architectures, the average time taken is 02:27 which in the terms of machine learning is very minimal.

The tumor is detected as the yellow marking is the tumor in the CT scan data and it also detects the liver which is marked in sky blue color. If there is no tumor on the liver it will simply display the result in the form of liver image only (which is in the sky-blue color). This will help to detect liver and tumor easily for the medical experts.

VI. CONCLUSION

Several deep-learning models have been developed to detect and segment liver and liver tumors early. There is a need for automated algorithms for segmentation in order to come up with a precise radiation therapy treatment plan. Researchers in the past have mainly been using contrast-enhanced diagnostic CT images with an intent to feed them into neural networks that can be used to diagnose liver tumors based on the inputs.

However, we have processed CT scan images using U-Net with model FastAI. For liver segmentation and tumor segmentation from liver CT scan images respectively, accuracy of 99.7 percent(approx) were obtained. One factor of degradation of accuracy is liver not present in CT scan images.

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