Liver Tumor Segmentation and Classification

Vidhi Kokel
Department of Electrical and Computer Engineering
Queen's University
Kingston, Canada
20vjk@queensu.ca
Student ID: 20241891
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***Abstract*—Cancer is the leading cause of deaths throughout the world among the people younger than 70 years. Of all, liver cancer contributes its significant share to the mortality rates in the patients affected by cancer. This paper analyses a robust and accurate deep learning(DL) technique called Dynamic UNet to detect a cancerous or say tumorous portion of the liver from a full-body X-ray computed tomography (CT) image. The proposed approach consists of extracting the area of liver from the full-body CT with subsequent pre-processing of the image. Once the image is pre-processed, our method employs the mentioned approach for segmentation of the image pixels into 3 major classes i.e. Background, Liver, Tumor. We also employ conventional machine learning (ML) techniques like random forest and decision tree classifiers as well to experiment and compare their accuracy as well as performances. After our analysis of the performance of the mentioned techniques, Dynamic UNet has been proved to be the most accurate.**

Keywords*—liver, tumor, image segmentation, image classification, cancer, dynamic unet, randomforest. decision tree

I. Introduction

Cancer is one of the most dangerous diseases causing huge number of fatalities worldwide. Of all the cancers, liver cancer is considered as the second most common cause for deaths due to cancer. Nutrition, Physical activity and diet affect liver cancer risk. [1] Liver cancer is difficult to detect at its early stages since it does not usually represent the symptoms. Hence, diagnosing the disease as early as possible becomes more critical for the health of the patient, otherwise it might deteriorate at an increasing rate which might not be possible to control.

Artificial intelligence has made revolutionary progress in the domain of medical imaging and diagnostics. There are multiple studies contributing to diagnosing multiple diseases, proposing new and minimal invasive techniques. Many of them just use the existing technologies like Computed Tomography (CT), Ultrasound images etc. and propose a classification technique in order to detect if a specific body part is unhealthy. Several studies have also been made to detect unhealthy Liver or say to detect a liver affected with cancer. For instance, Biswas et al. [2] and his team proposed a deep learning paradigm that helps classifying a diseased liver whereas Lamb et al. [3] used Dual Energy CT (DECT) for the classification.

In this paper, we have applied the deep learning concept of Dynamic UNet to segment each pixel of the liver CT image into a healthy or unhealthy one. Additionally, we have also used the conventional classification techniques: Random Forest and Decision Tree, to perform a comparative study on which technique gives a better accuracy for detecting a cancerous liver.

The layout of the paper is as follows. Section 2 describes the related work done for liver tumor segmentation or classification using various techniques while Section 3 discusses about the detailed methodology of the proposed approach along with two other conventional classification techniques. This is followed by a detailed analysis of the performance of all the mentioned techniques in Section 4 and the discussion is covered in Section 5. Lastly, this study is concluded as part of Section 6.

II. Related Work

Studies have been done in both, the detection of cancer as well as detection of liver cancer specifically using artificial intelligence techniques. Many of them use conventional machine learning techniques whereas some of them try their luck in the domain of deep learning and use a deep learning paradigm to detect the unhealthy areas of the body using existing testing technologies like CT scans, Ultrasound etc. These studies undergo various steps of pre-processing to extract the relevant features and the specific area of interest which is followed by the logic for segmentation or classification of whether it is an image of a healthy or an unhealthy patient. Following are the briefs of some of many such studies.

Biswas et al. [2] and his team used ultrasound liver images and proposed a deep learning framework for liver tissue characterization and stratification. This DL framework uses inception model for dimensionality reduction and speed of its network without impacting the cost of computing. The images used in this study were optimized by stripping a percentage of its background and the proposed framework showed remarkable accuracy with 15% of its borders stripped. This study also compared the proposed DL framework with SVM and ELM ML techniques with respect to various aspects like accuracy, reliability etc. where DL outperformed SVM and ELM in all aspects except time. The proposed system was cross verified by analyzing various cross validation methods (K2, K3, K5 and K10) as well as its accuracy has also been validated using biometric facial datasets available universally.

Lamb et al. [3] and his team underwent a study for assessing liver fibrosis from Dual Energy CT images by combining the "multi-material decomposition" (MMD) algorithm with a biologically driven hypothesis. They performed this study on a group of twelve-patient and it produced quantitative maps showing the spatial distribution of liver fibrosis, as well as a fibrosis score for each patient with statistically significant correlation with the severity of fibrosis across a wide range of disease severities. The application of this algorithm to longitudinal DECT scans of the patient group produced good results. Finally, they claim that their algorithm can successfully stratify patients with liver fibrosis and can serve to supplement and augment current clinical practice and the role of DECT imaging in staging liver fibrosis.

Dong et al. [4] and his team proposed a Hybridized Fully Convolutional Neural Network (HFCNN) for the segmentation of liver lesions from CT images which can be used to assess the tumor load, plan treatments predict, and monitor the clinical response. Their method includes the successful extraction of features from Inception combined with residual and pre-trained weights. This deep learning system shows the concept of illumination portions of the decision-making process of a pre-trained deep neural network, through an analysis of inner layers and the description of features that lead to predictions.

3D CT images were used by Huang et al. [5] and his team for detection and segmentation of liver tumors with help of a machine learning technique Extreme Learning Machine (ELM). In this study, the automatic detection of tumor was formulized as novelty detection by training the ELM with only healthy liver samples and later it was compared with an ELM model trained with two-class classification issue. This study identified each voxel and assigned it with a label: either a tumor class or nontumor class. A voxel is represented with a rich feature vector that distinguishes itself from voxels in different classes in this study.

Thus, as discussed above, various studies have been conducted to detect the liver tumor segmentation and this study is one more attempt on finding an optimal solution for the diagnosis of a liver tumor.

III. Methodology

Overall methodology of this study mainly consists of data pre-processing, machine and deep learning-based modelling, and model evaluation and selection to automate tumor detection in CT-imagery. Fig. 1 shows the general flow of methods for this study. The dataset for this study is obtained from a Kaggle competition (https://www.kaggle.com/andrewmvd/liver-tumor-segmentation) [6]contains 130 CT images of 8 patients.

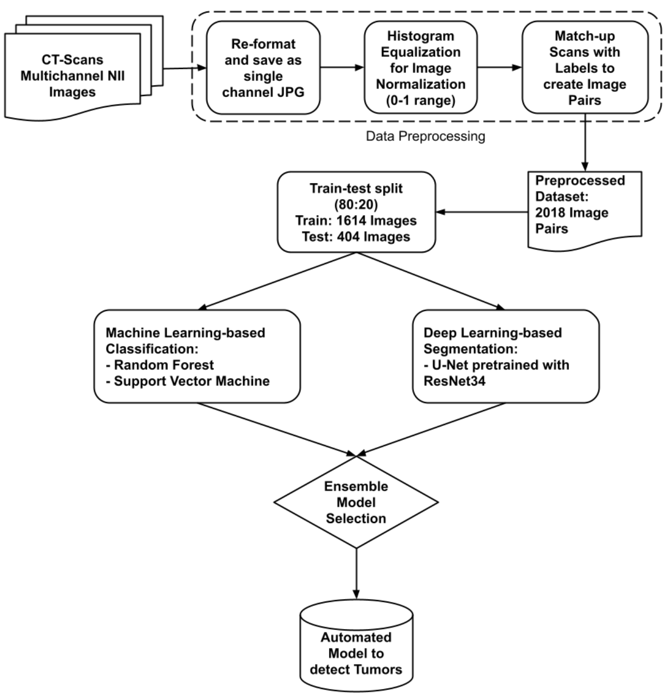

Fig. 1. Architecture of the proposed system

A. Data Pre-processing

A CT Scan image is actually a combination of images captured at different frequencies, and are usually stored in a multi-channel (NII) format. To start with, all the images are converted into a 3-channel JPEG format from the multi-channel NII format. The labels for this dataset are provided as a set of polygon-based pixel locations for each image, which are then parsed and a 'label-mask' is generated in the form of binary image, and then each label mask is paired with the CT-image. Further, to account for all the different frequencies in a CT-image, the JPEG CT-images are normalized using histogram equalization for the range 0-1. This results into a pre-processed dataset comprising a CT-image and a corresponding 'label-mask' image of 2018 such image pairs. Fig. 2 shows all the different stages of an image when it goes through the above-mentioned steps of pre-processing.

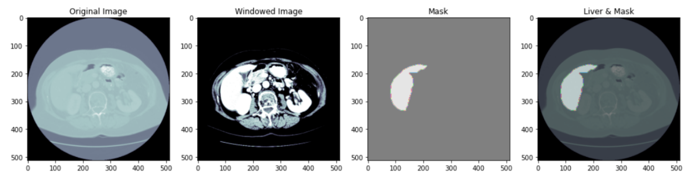

Fig. 2. Pre-Processing and Classification of CT Images

B. Training the network

Deep learning always comes with the cost of high resource and time consuming training. In order to reduce the number of resources used and time consumption, the concept of cyclical learning is used in this study to find out the most effective learning rate.

The pre-processed data was split into a training set and testing set with a ratio of 80:20 resulting in a set of 1614 images for training the network. Initially, the encoder of the Dynamic U-Net was initialized with the weights of the pre-trained ResNet34, forming the dynamic Res-U-Net using transfer learning. Then the network was frozen and fine-tuned for 5 epochs using cyclical learning. Fig. 3 represents a graph of the loss with respect to different learning rates and highlights a good learning rate for the model. Moreover, the provision of fallback was also made available during the training process to allow the model to be reverted its previous state if the consecutive epoch did not result in a better version of the model.

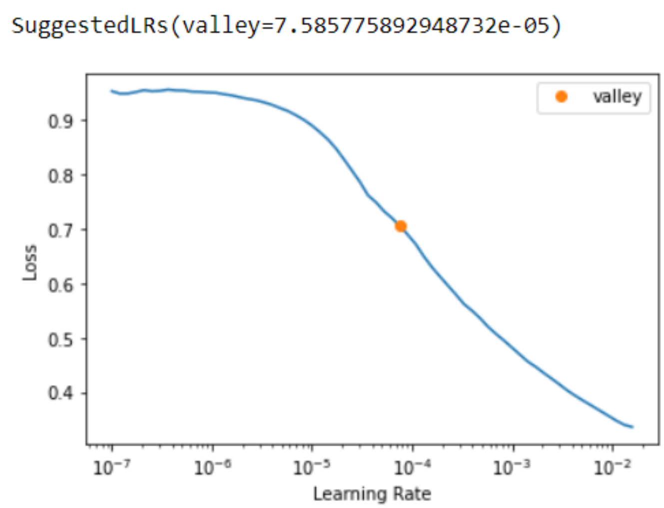

Fig. 3. Suggested learning rate using cylical learning

C. Segmentation and Classification

This study treats the problem of tumor detection as both a classification based problem and a segmentation based problem. The former is implemented with Machine Learning-based algorithms and latter with Deep Learning-based algorithms. There are consistent trade-offs in pursuing this computer vision problem as a classification problem and a segmentation problem. While classification does not require any contextual information, there is a pronounced risk of overfitting. On the other hand, segmentation almost entirely learns on the derived and contextual information and has a high time and resource overhead. But with little to no risk of overfitting it almost always proves to give a higher performance. Fig. 4 shows the set of target training image while prediction with its respective predicted image.

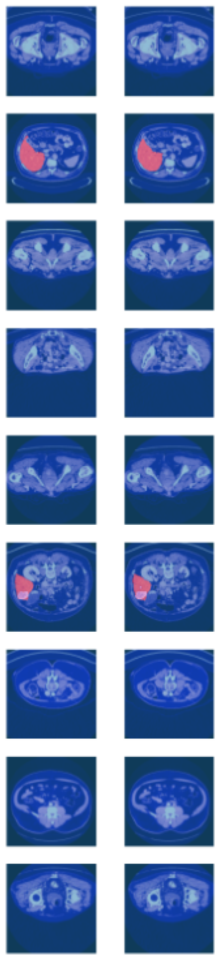

Fig. 4. Training input and its respective prediction

D. Testing

After successfully training the respective deep learning and machine learning models, we perform the testing of some sample images and check if a tumor could be detected. Fig. 5 shows an input image of one such sample and Fig. 6 represents the predicted output for the same. It could be clearly seen that the tumorous area is successfully detected.

Thus, this study uses the concept of cyclical learning with Dynamic-UNet to find a good learning rate for the network and compares its results with the results of the conventional classification techniques.

IV. Performance

The segmentation and classification techniques are evaluated in this study on the basis of their accuracy which is calculated using the formula shown below.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

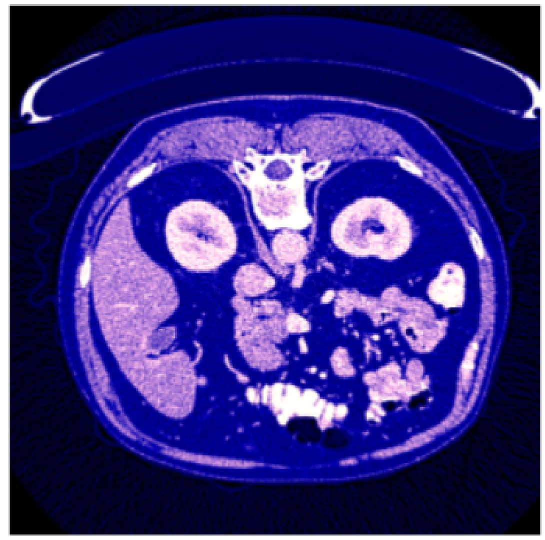

Fig. 5. Testing input

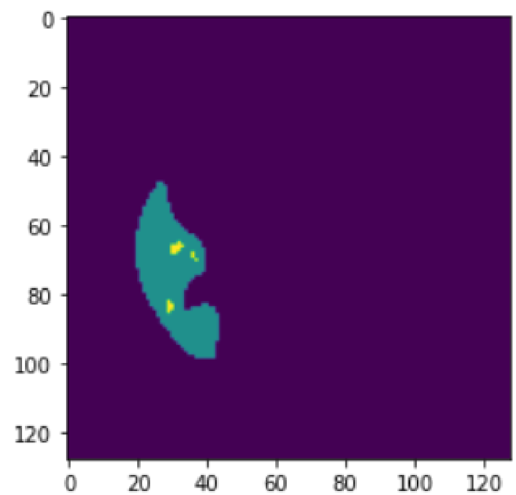

Fig. 6. Testing Output

Table 1 represents the accuracy of all the three techniques used in this study respectively. All the three techniques performed relatively good. Of all, Dynamic UNet DL technique and Random Forest showed a competitive accuracy while Decision Tree failed to match up to their accuracy.

TABLE I
MODEL ACCURACY

Learning paradigm	**Model**	**Accuracy (%)**
Deep Learning	Dynamic UNet	96.8
Machine Learning	Random Forest	96.4
Machine Learning	Decision Tree	92.1

V. Discussion

The main focus of this study was to specifically look for a tumorous liver by analysing the CT images and classifying each pixel of it, thus highlighting the exact location of the tumor. This technique could be made more robust by validating it with various other datasets available. Moreover, different formats of the images could also be taken into consideration for the future work of this study. Once, this study is proven to be giving good results considering various metrics, this study could further be extended to detect tumors of other organs of the body.

VI. Conclusion

In this study, we used 130 CT images of 8 patients, that were in NII image format, as the dataset to perform segmentation and classification of each pixel of the image into whether it corresponds to a healthy liver tissue or a tumorous one. To achieve this, we performed various pre-processing techniques like converting the images into JPG format, histogram equlization and matching the images with their respective labels by creating respective masks. Moreover, we used DL technique like Dynamic UNet along with the concept of cyclical learning to find the optimal learning rate and compared it with the conventional ML techniques Random Forest and Decision Tree. From the results, it can be clearly seen that the deep learning technique outperformed the conventional techniques in terms of accuracy and it can be considered as a good solution for liver tumor segmentation.

VII. Code

The code for this study can be found in this git repository: https://github.com/Vidhi2014/Liver-Tumor-Segmentation. Following are some of my code citations:

- Liver Segmentation with fastai v2 by Arunas Naujokas
- Object-Oriented-Deep-Learning-for-Building-Extraction by Chintan Maniyar

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