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Research Article

Web based Liver Cancer CAD system for Deep Learning using Convolution Neural Networks

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Abstract

Liver cancer can be broadly classified into two types. They are primary and secondary liver cancers. Hepatocellular Carcinoma (HCC) is the most common type of primary liver cancer. Detection of liver cancer from CT images is a sophisticated work for the radiologist. A web based Liver CT image processing for online processing without losing vital information is the objective of this paper. The volume and dimensions to be considered in liver CT images may also be reduced for efficient feature extraction and faster diagnosis of Liver cancer. The most common CT image file format DICOM or NifTi is converted to PNG file before the preprocessing step. The commonly used preprocessing techniques considered before introducing the 2D or 3D feature map to a CNN are also discussed here. The changes in gray levels are used to detect lesions in liver tissues with HCC. The imbalanced data set gives us poor classification accuracy. Data augmentation must be carried out using addition of noise or morphological operations in these CT images in case the sample size is less for the training dataset.

Keywords: Computed Tomography(CT), Hepetocellular Carnicoma (HCC), Computer Aided Diagnosis (CAD)

INTRODUCTION

Liver cancer is the sixth mostly detected cancer and third most leading cause of cancer in worldwide statistics of 2020[1]. HCC is detected in 90% of the diagnosed liver cancers [4].

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Less than 15% patients having liver cancer can survive without treatment [23]. The liver cancer CAD systems can be broadly classified as manual, semi-automatic and automatic[7]. The commonly used DICOM file with large size and slower interpretation is the bottleneck for several CAD systems. Automatic or semi-automatic CAD systems are preferred as compared to manual segmentation and corrections[7,16,18,20]. The proposed online system will help to diagonise an image with a better representation and faster processing.

Pre-Processing of liver CT images is a crucial step before feeding to a CNN. The importance of this step is that liver must be correctly segmented from other adjacent organs such as spleen, heart, abdominal wall and stomach [17,18,19,23]. Liver also has high anatomical variability [12][19]. Liver is of heterogeneous sizes and voxel resolutions [12]. There is a low contrast between Liver and neighboring organs [18,20,21,32].

The CAD systems should also avoid missing small lesions(<10mm)[7][19]. Lesions also differ in density, shape ,size, appearance, localization, perfusion and echo[5,7,8,25,30]. The contrast of Liver cancerous portion in a CT scan is less compared to the healthy tissues [16].

CT scan involves the movement of the X-ray beam through the detector [15]. CT images considered are images along the sagittal, coronal and axial planes [19]. Single phase CT consists of the CT images taken usually in the Portal Venus(PV) phase. Multi-phase CT in HCC images considered are Non-contrast(NC), Arterial(ART) ,Portal Venus(PV) and delay phase[6,11,13,17]. There are only a few studies on Multi phase CT [12]. Multiphase CT gives better segmentation than single phase CT for the liver[12]. CT images shows aberration due to difference in spatial orientation, respiratory movements, body position and heart rate of the patient [13]. The CAD systems should also be able to distinguish between benign liver lesions (Hepatocellular Carcinoma(HCC), Metastasis(MET), Cholangiocarcinoma(CC) and cancerous liver lesions Hemangioma(HEM), Hepatic Adenoma(HA), Focal Nodular Hyperplasia(FNH) and Abscess(ABS)[18].

LIVER CANCER CAD SYSTEM

A liver cancer CAD system check changes in grey scale values of liver tissues in the CT scan [2]. The HCC in Liver are characterized based on its size in millimeters (mm). The Liver CT images must go through different stages before detecting the presence of a benign or malignant lesion. An annotated training dataset by an experienced radiologist is preferable for a CAD system [5]. Dataset is divided to training and testing data and cross validation may be done [26,30]. Imbalanced data set gives us poor classification accuracy [3]. There are only a few publically available datasets prepared by experts for training and testing [19,24]. Data augmentation is done to avoid over fitting in such situations. Segmentation of the liver contour and liver lesions must be carried out as the next step. These two steps employ the use of CNN for classification. The feature map selected as input to a CNN must be appropriate enough to classify a lesion with HCC as benign or malignant within the scope of this study.

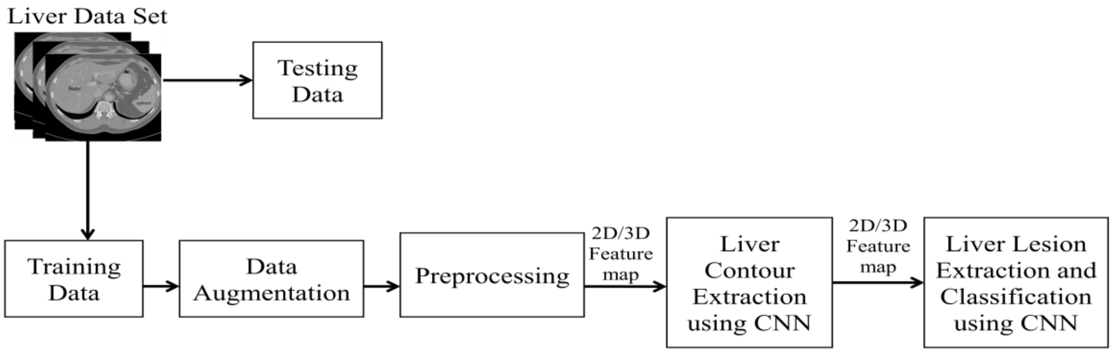

FIGURE I : Liver cancer CAD system using CNN

DATA AUGMENTATION

Data augmentation will help the network to be trained with the required invariance and robustness [30]. It is always better to collect as many training data as possible. Less number of training data samples results in overfitting [5,34,29]. Data augmentation is done in most of the works as there are less number of publically available datasets [1,11,31].

Poor classification for minority classes is also present in case data augmentation left out for a CAD system. Augmented data to be considered for minority classes are rotate(-15^0 and 15^0) and addition of Gaussian noise σ(0.9 to 1). [2,3]. Mirrored images and rotated images[5], affine transformations like flipping, rotating and mirroring and augmentation of colour values[19],crop and resize[11], addition of noise[21], cropping and left-right flipping[21] are also used for data augmentation. The creation of synthetic images for synthetic data augmentation [30], is achieved by a sophisticated network, Generative Adversarial Networks (GANs) [29]

PREPROCESSING

Preprocessing aims to remove background, noise levels, film artifacts (annotations) and contrast enhancements [35]. Low contrast, weak edges and high noise is a major challenge in preprocessing [20]. CT images have intensity values in Hounsfield units. The only preprocessing done for the fully connected CNN was normalization to (-200HU, 200HU) Hounsfield unit (HU) intensities in this work [21]. Some authors have normalized the Hounsfiled unit(HU) intensities to the range (-100HU, 400HU) [12,19,21]. This normalization operation is termed as windowing. DICOM file is converted to other file formats such as PNG, a lossless compression is mostly preferred as it preserves data [19].

DICOM to NIFTI[27] or JPEG[11] are the other file format conversions**.** DICOM file conversion to image format gives us the flexibility to utilize already existing state of the art operations which aids in detecting liver lesions**.**

Basic morphological operations such as cropping, resizing[5,19] and scaling [12] may be applied. Small holes and islands can be removed using morphological operations[10]. Other operations are contrast enhancement through histogram equalization [21], window width and level[14], resampling[21], Bilinear interpolation [31] is also considered for CT image preprocessing. Binary lesion, non lesion mask [7] and guided filter [4] can sharpen liver image structure. Normalization to gray scale values from 0-255 is also performed during preprocessing [17]. Around 150 slices are present in a CT volume [25]. Some preprocessing operations were done using voxels [7]. Dimensionality reduction for feature reduction is achieved by PCA[26], DWT and SVD in CT images[31].

Histogram equalization on each CT slice is seen to be biased to the varying proportions seen in each slice of the liver [12]. Preprocessing is an important step and some authors prefer minimal preprocessing for faster results and some have reported better accuracy [18,20]. The preprocessing phase should foresee segmenting liver contour and liver lesions [35].

CONVOLUTIONAL NEURAL NETWORK

The Convolutional Neural Network works on input with activation function, convolution and pooling layers[19]. Pixel wise classification is more of encoder-decoder architecture and takes more time and memory for processing [19]. CNN uses 2D images as input[2]. This 2D image is called the feature matrix[2].

The input to a convolution layer is m x n x c, where m is the height, n is the width and c is the number of channels. Convolution layer extracts high level features and higher level extract low level features[5]. CNN convolution layer extracts feature map from the preceding layer [20].

Deep learning provides a non-linear function to process data. CNN based liver contour or tumor segmentation can be classified as 2D CNN and 3D CNN. The 2D CNN works with 2D convolutional kernels and the 3D CNN works with 3D convolutional kernels for processing the input. The CNN is data driven and it learns hierarchical features [24,30]. CNN can learn useful features from the beginning [20]. CNN will preserve edge features [2]. Most common CNN architectures are Resnet, AlexNet, VGG16[2,19,30] ,U-Net[33] and others are ResNet50[14], ResGlNet[13], Alexnet[31], Cascaded FCN[21] and the newly introduced 3D CNN[20,28]. 3D Conditional Random Fields (CRF) is employed as a statistical measure for prediction of lesions. Multi class CNN is also preferred for a single medical decision [31]. Pre-training, retraining and fine tuning may also be required in CNN [6].

LIVER AND LEISON SEGMENTATION

Liver segmentation checks whether each voxel or pixel is in the liver [28]. Most of the segmentation techniques to extract contour, work on biomarkers such as histogram or textual features. Liver mask is also computed using Bayesian classifier, morphological, active contours [10], marker controlled watershed algorithm[9] and 3D liver segmentation using modified region growing algorithm. The contour of a liver region can be refined with a fully connected Conditional Random Field (CRF)[23]. Semantic segmentation is also proposed for both liver contour and tumor extraction [33]. Both local and global features are considered for segmentation[8,13].

Lesions differ in density, shape and echo [5]. Lesions are found by checking grey levels of tissue in different phases [2]. Liver cancer segmentation can be done using Gaussian Mixture Model [9]. Multiphase CT can also have ROI extraction from the NC, ART and PV phases [17]. Segmented lesion is also resized before further processing [13].

ONLINE LIVER CANCER CAD SYSTEM

An online Liver cancer CAD system is deployed in python using the IDEs Spyder and Flask of Ananconda navigator. There is provison to navigate to Indian cancer society and American cancer society. The user can load the liver image to be diagonised by clicking the browse button.

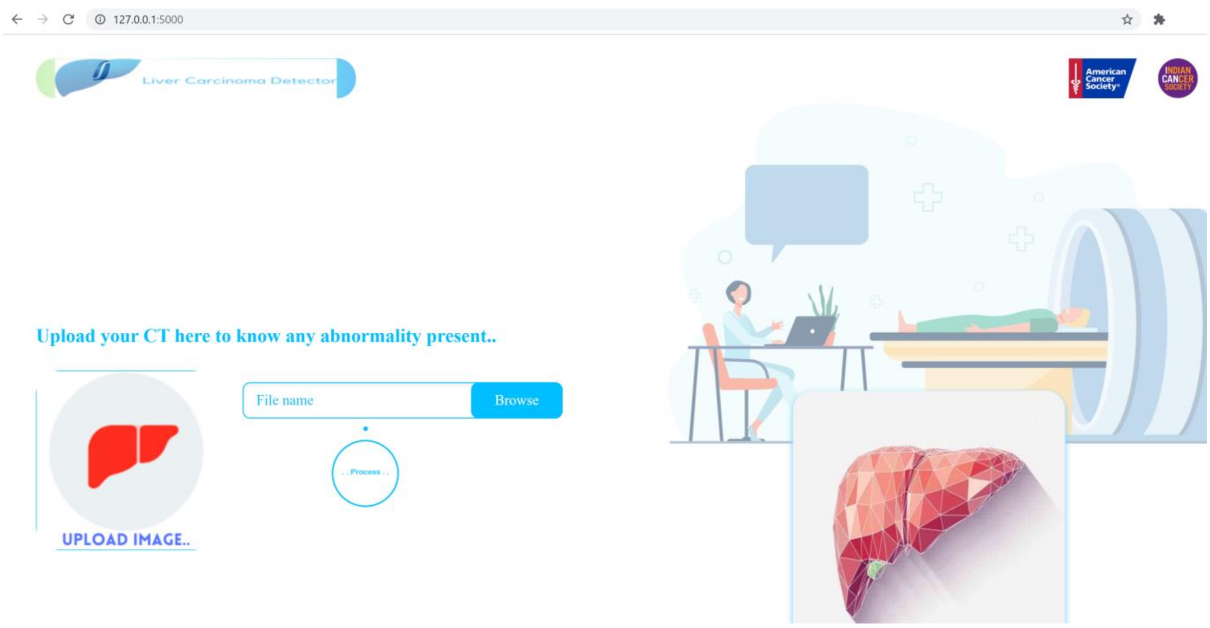

FIGURE II : Online Liver cancer CAD system using CNN

The browse button will inturn load the CT image to the upload area as in Figure II. Suitable images are mostly created or taken from online repositories for the webpage. A primary diagnosis such as benign, malignant or normal is to be given at this stage. Any CNN model can be deployed from Spyder IDE.

FIGURE III : Loading of CT image in the web interface

CLASSIFICATION ACCURACY

Statistical, Texture & Geometrical features are taken for many CAD system classifiers [13,14]. Texture features are found to be more accurate [9,17]. But texture feature computation is computationally intensive [17]. Semantic pixel wise classification is also performed [19]. The authors also affirm that feature vector must include information from all phases [18]. Lesion based classification is also done using SVM [13]. The authors propose that a single FCN may used to segment liver contour and another to segment liver lesions as benign or malignant(HCC) [7,19,30,33]. The classification accuracy must be taken with respect to annotated liver CT datasets with the help from radiologists. Ground truth images are preferable to check the efficiency of any proposed CAD system.

TABLE I: Comparison of tumor classifier accuracy for Liver CT images

Sl.No	Author	Year	Classifier	Dataset	Accuracy
1	S Almotairi et al.[19]	2020	Modified SegNet	3D-IRCADb-01	86%
2	Peng J et al. [7]	2020	ResNet50	Nan Fang and Zhu Hai hospitals	84.3%
3	Li J et al [2]	2019	LeNet-5 CNN	Data set confidential	98.4%, 99.7% & 98.7% (Diffuse, Nodular & Massive HCC)
4	Das A et al [9]	2019	Sequential DNN	IMS and SUM Hospital, India	99.38%

5	Ouhmich et al [12]	2019	Cascaded U-Net	Db	91.8%

CONCLUSION AND FUTURE SCOPE

Online CAD system with deep learning using CNN for Liver CT Tumor detection as benign, malignant or normal Liver is the scope of this study. There are no such online CAD systems for Liver cancer detection which are publically available. The proposed online CAD system is based on CNN and should be able to segment liver contour and tumors precisely. Liver CT scan, medical datasets where the publically available datasets is very less still remains a challenge. Data augmentation and preprocessing have been proposed. Commonly employed CNN models are taken into consideration for segmentation of Liver contour and lesion. The lesion is also classified using CNN. The aid of radiologists and ground truth images are also considered. The volumetric size calculation of the lesion is a challenging work for any CAD system. Both supervised and unsupervised deep learning methods need to be explored. Post processing can also reduce false positives.

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