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Survey on Approaches to Deal with Limited Dataset for Liver Lesion Classification Using Deep Learning

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Abstract: - The one of the prominent cause of death in all over the world is Liver cancer. Various medical imaging techniques such as X-rays, Computed tomography (CT), ultrasound (US), magnetic resonance imaging (MRI) are now available for detection and categorization of liver tumor. The manually detection of liver tumor is a challenging task and time intensive. There are plenty of works has been done using Computer aided diagnosis (CAD) systems based on these medical images with deep learning which enhanced the liver tumor detection performance ratio. Due to non-invasive and cost effectiveness, CT image is widely used in liver tumor detection. The one of the major advantage of deep learning is that they extracts low and high level features from underlying data automatically rather than feeding handcrafted feature extraction techniques. Although there are several issue with deep learning. One of the barrier with deep learning is the requirement of large annotated data set but in medical field, mostly the available annotated image data set is limited. The objective of this paper to provide an overview of various methods to cope with this barrier especially in liver lesion detection and classification.

Keywords: Computer aided diagnosis (CAD) system, Computed tomography (CT), Deep learning (DL), Liver lesion.

I. Introduction

In recent era, Cancer is one of the devastating illnesses that threats human life. The World Health Organization (WHO) has published a statistics about death causes by cancer in the future. They estimate 11 million people are dying due to cancer in the 2030. By 2025, it's anticipated that India would be known as the "global capital" of liver disease [1-2]. Because the liver is resistant to early identification and therefore continues to operate even when partially injured, the condition is considerably more serious because by that point it may have already done irreparable harm. As a result, it becomes critical to make an early diagnosis of liver problems so that timely treatment is possible. Various medical imaging techniques like CT scan, MRI and US available for capturing the images of the liver [3]. Among these techniques, our focus is on CT. Due to the cost effectiveness compare with MRI and better performance compare with US image, CT image is the most widely used in liver tumor detection [4-6].

Various Computer-based systems like Computer Aided Diagnosis (CADx), Computer-Aided Detection (CADe) and Content-Based Medical Image Retrieval (CBMIR) are proposed by researchers to assist a radiologist in interpreting the CT images. The CADe systems only discover the suspicious areas like tumor in an image, whereas the CADx systems not only discover suspicious areas but also specify types of detected tumor (for instance, malignant/benign) [7-8]. The Computer-Aided detection and Diagnosis (CAD) systems are commonly used to represent both CADe and CADx system. The CAD systems gives a faster and precise diagnosis hence workload of radiologists is reduce. The CBMIR systems mostly used to retrieve similar images from dataset based on given radiological features [9]. The main focus of this review is on the CAD systems.

The rest of this paper is structured as follows: The overview of CAD system discuss in Section 2. Section 3 covers various deep leaning approaches to liver lesion diagnosis. The performance analysis represent in Section 4. Section 5 represents conclusion of the study.

II. COMPUTER AIDED DIAGNOSIS SYSTEM

The CAD system for liver cancer detection is depicted in Fig. 1.

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The primary goal of the preprocessing phase is to improve the quality of the collected CT images to produce precise results in the next steps. In the reviewed literature, the research gives major focus on data augmentation, Image denoising, resizing, normalization and contrast enhancement [11-12].

Segmentation is a vital step which separates the desired anatomical or pathologic regions from the image. Improper segmentation can ultimately result in misdiagnosis. In the reviewed literature, semi-automated, fully-automated, or entirely manual segmentation methodologies were used. In manual segmentation, the radiologist outlines the lesions manually during segmentation, but this takes a lot of time and is subject to inter- and intra-operator variation [10]. However, manual contouring has been used extensively in the published literature. Some researchers have only performed liver segmentation and skipped lesion delineation. However, because to the tight affinities between the liver and its neighbouring organs, notably the heart and stomach, segmenting the liver is itself quite difficult. Automatic segmentation is a two-step process that separates the liver from the abdomen first, then segments lesions from the segmented liver.

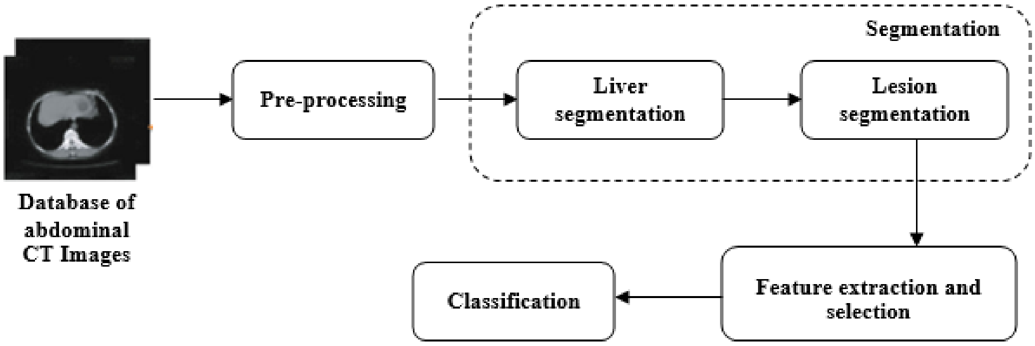

Fig. 1: Systematic outline of CAD based liver cancer detection system

Most of the researcher used Gray Level Co-occurrence Matrix (GLCM), Laws' Texture Energy Measures (LTEM), fractal and histogram based methods, Local Binary Pattern (LBP) and Gray Level Difference Matrix (GLDM) to extract the features from segmentation output. The Deep learning based approach does not needed hand-crafted feature extraction techniques as internally it is captured in Deep learning architecture as shown in Fig. 2.

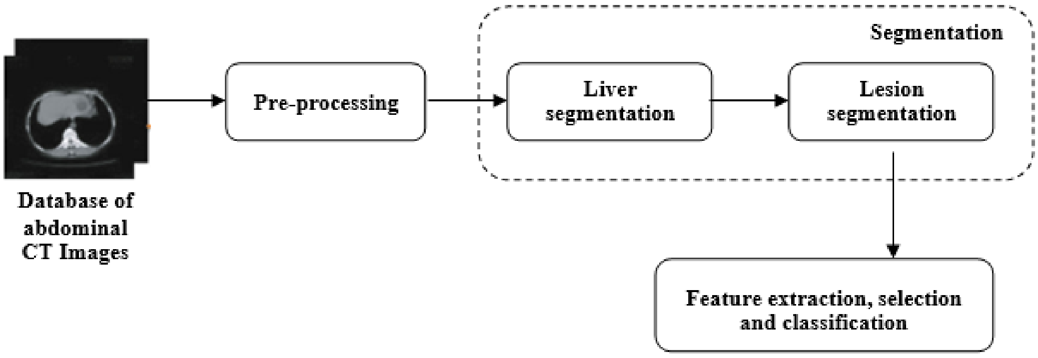

Fig. 2: Systematic outline of Deep Learning based CAD system for liver cancer detection

III. CURRENT STATUS OF COMPUTER-AIDED LIVER LESION DIAGNOSIS

There is no publically available liver CT image data set who contain ground truth value for liver lesion types, hence all the works till know done on liver lesion classification based on private data set. Although Liver and lesion segmentation CT image public data set with ground truth value like LiTS’17, 3D- irDircadb [13-14] available which used by researcher to evaluate segmentation results. This review analyses and reports various studies using deep learning techniques. The majority of authors have suggested CNN-based architectures which perform better.

One common barrier for using deep learning is the requirement of large annotated dataset to train a model. Many researcher tries to cope with this barrier by using following methods

- Deep learning with transfer learning (pre-trained model)

- Patches extraction from CT image
- Data augmentation
- Hybrid approach

A. Transfer Learning Approach

In this approach, by altering the network's architecture, we could employ a pre-trained model like AlexNet or VGGnet and adapt it for a different application [15]. By making certain adjustments to the pre-trained network based on our application, we may utilize AlexNet, for instance, to categorize some more classes outside those 1000 classes on which AlexNet trained.

In order to classify hepatic lesions using the deep features, Lakshmi Priya.B et al.[16] suggested an ensemble FCNet classifier (GoogleNet –LReLU transfer learning approach). Through the multi-temporal image fusion of the HA and PV phase and decorrelation stretching operation, they improve the image. Using a dynamic colour gradient thresholding technique, liver lesions are segmented. In the current GoogleNet Model, they made three modifications: To significantly improve the performance of the classifier, leaky ReLU activation functions are used in place of ReLU activation functions in the inception modules, a stack of three fully connected layers is added before the classification layer, and deep features of various levels of abstraction are extracted from the output of each inception layer and provided as classifier input. Convolutional neural networks are used by Shengqing Zhai et al [17] to extract lesion characteristics from CT scans, and the CaffeNet network model is used to recognize and categorize images of liver illness. Histogram equalization and median filter-based image de-noise methods are used as pre-processing techniques. A pre-trained residual convolutional neural network (ResNet) has been suggested by Weibin WANG et al.[18] to classify liver lesions. According to the outlines of the liver tumours marked by skilled radiologists, the author extracts the areas of interest (ROIs) from three phases of CT images (NC, ART, and PV).

B. Patch Extraction from CT images

Another approach to deal with limited data set, provides two types of ROI as input: local information in form of patches of different size from liver lesion and global information where entire lesion considered.

Dong Liang et al. [19] have suggested a unique residual CNN with global and local pathways (ResNet-GL) model for differentiating various types of localized liver lesions. Both individual lesion patches and the whole lesion region are used as inputs to the model (local and global information). Using an interactive segmentation technique based on random walks, the lesion is retrieved. In feature extraction, the ResNet-GL is utilized to extract features from both patched and entire lesions. For the task of classifying focal liver lesions in multi-phase CT images, Lanfen Lin et al. [20] proposed a deep learning framework called ResGL-BDLSTM that combines a residual deep neural network (ResNet) with global and local pathways (ResGL Net) with a bi-directional long short-term memory (BDLSTM) model. The most representative features from each single phase CT image and each multi-phase CT image are extracted using ResGLNet and BD-LSTM, respectively. Wen Li et al [21] have proposed CNNs based approach to detect lesion where CNN used to segment lesions from CT image. Hand-crafted feature extraction techniques applied to extract features for lesion. The results of CNN compared with Random Forests (RF),AdaBoost and support vector machine (SVM) which show that CNN has better performance compared with other these three methods.

C. Data Augmentation Based Approach

It enlarge the size of data set by generating synthesized images from existing data set using either traditional geometric transformation like scaling, rotation, Flipping, Translation, etc or Deep Learning Model like GANs(Generative Adversarial Networks).

To increase the effectiveness of learning, Hansang Lee et al. [22] have suggested a synthetic data augmentation method called Lesion INformation Augmented (LINA) patch employing mask-to-image translation based on pix2pix and DCGAN-based lesion mask synthesis. To classify lesions, a multi-scale CNN were trained on LINA patches of different mini-patch sizes. A hybrid approach employing Convolutional Neural Networks (CNN) and Discrete Wavelet Transform- Singular Value Decomposition (DWT-SVD) based perceptual hash functions has been proposed by Akif Dogantekin et al. [23]. To create synthetic images, the traditional geometric transformations (flipping, rotating, and shearing) are used. The DWT (Discrete Wavelet Transform) and SVD (Singular Value Decomposition) based perceptual hash functions, with sizes of 16 x 16, 32 x 32, 64 x 64, and 128 x 128, are used as dimensionality reduction. A technique for creating synthetic medical images using generative adversarial networks (GAN) and classifying liver lesions using CNN has been proposed by Maayan Frid-Adar, et al. [24]. The dataset was augmented using traditional methods such as translation, rotation, flipping, and scaling. Those images that produced the desired results were then taken into consideration in the second step, which involved applying deep convolutional GAN to create synthetic images of lesions.

D. Hybrid Appraoch

Combination of more than one approach i.e fine tuning with data augmentation, local and global information with fine tuning are used to deal with limited data set. Some of the research used handcrafted feature extraction techniques output of these are given to deep learning architecture for classification.

An end-to-end pre-trained deep network for liver lesion categorization s has been proposed by Franisco Perdigon Romero et al [25]. Geometric transformation is used to create the synthesized images, including rotation (up to 30 degrees), horizontal and vertical shift (up to 25 pixels), and flipping. A convolutional neural network based on Inception-V3 was created, and it comprises fully connected classification layers that provide probabilistic outputs. The network was trained from scratch using pre-trained weights from the ImageNet dataset. A multi-class convolutional neural network has been suggested by Idit Diamant et al. [26] to classify lesion. By flipping the data to the right or left and rotating it through [5, 130, 300] degrees i.e. traditional data augmentation is used to enhance the lesion class. With the assistance of a professional, patches are extracted into three types: normal boundary area, normal interior area (non-lesion class), and lesion boundary (lesion class). Amita Das et al. [27] have suggested a novel method for classifying liver lesions using deep neural networks (DNNs) termed watershed Gaussian based deep learning (WGDL). From 225 CT images, the liver region was extracted using the marker controlled watershed segmentation technique [19, 20] and morphological operations. The cancer region was then separated from the liver area using the Gaussian mixture model (GMM). Using the GLCM approach, statistical, geometrical, and texture information were collected from the segmented images and provided as inputs to the DNN.

IV. Performance Analysis

In the literature, there are a number of performance metrics are used to evaluate model. Commonly used terms include sensitivity (recall), specificity, precision, and accuracy. They are defined as follows:

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

$$Sensitivity\ (Recall) = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{\mathrm{TN} + \mathrm{FP}}$$

$$Precision = \frac{TP}{\mathrm{TP} + \mathrm{FP}}$$

True Positive (TP) is the sum of counts where both the expected and actual values fall into the positive class; True Negative (TN): The total counts where both the expected and actual numbers fall into the negative category; False Positives (FP) are total counts when the predicted class is positive but the actual class is negative. False Negatives

(FN) are total counts that are predicted to be in the negative category but are really in the positive category. The performance analysis of section 4 is represented in Table 1

TABLE I. PERFORMANCE ANALYSIS OF VARIOUS APPROACHES MENTIONED IN SECTION 3

Method	Author	Performance Measure	Remarks
Transfer Learning	Lakshmi et al.[16]	Accuracy: HA Phase: 89.58% AP Phase: 87.22% After Enhanced Image: 97.37%	Two stage Enhanced Images gives better result instead of considering only AP or HA phase image
	Zhai et al [17]	Accuracy: AlexNet: 75.67% CaffeNet: 96.67%	Compare with AlexNet , CaffeNet gives good performance
	WANG et al.[18]	Accuracy: before fine-tuning : 83.7% After fine-tuning: 91.2%	With limited data set (388) Fine-tuning gives better result compare with without fine tuning
Patch based Approach	Dong Liang et al [19]	Accuracy: 87.58% (4 different classes of lesion considered)	Size of patches and number of patches extracted may affect the classification accuracy.
	Lanfen Lin et al [20]	Accuracy: ResGLNet: 88.05% ResGLNet and BD-LSTM: 90.83%	Multiphase images gives slightly better result compare with single phase but overall time complexity of the approach is high
	Wen Li et al [21]	Dice: 80.06% Precision: 82.67% Recall: 84.34%	Data set contains only 30 PV phase image
Data Augmentation based approach	Hansang Lee at al [22]	Accuracy: 87.30% Sensitivity: 86.72% Specificity: 87.71%	Only Single PV phase CT image considered.
	Akif Dogantekin et. al [23]	Accuracy: ELM: 97.30% SVM: 96.4% KNN:91.8%	145 single phase CT image with two class benign and malignant considered
	Maayan Frid-Adar, el al. [24]	Accuracy: Without augmentation: 57% Data augmentation using Geometric transformation : 78.6% Data Augmentation with GAN: 85.7%	The complexity of the training process was raised by the author's independent GAN training for each lesion class.
Hybrid Approach	Francisco Perdigon Romero et al [25]	Accuracy: 96%	Transfer learning and Data Augmentation approach used.

	Idit Diamant et al. [26]	Hierarchical multi-class CNN Sensitivity: 86% Binary-class CNN Sensitivity: 80%	By removing small size lesion TPR is improved to 93% Patch + Data Augmentation
	Amita Das et al.[27]	Accuracy: 98.38% Sensitivity: 100% Specificity: 97.72%	Handcrafted feature extraction techniques + Traditional Segmentation Techniques + deep learning

V. CONCLUSIONS

This paper gives us basic idea of existing work on dealing with one of the issue of deep learning model to cope with limited annotated data set for liver lesion detection and classification. All the researcher used private data set for liver lesion classification. Deep learning with fine tuning approach eliminates the need to train the Model from scratch but it is only appropriate when source domain on which model is trained and the target domain on which we want to use the model are relate to each other. Patch extracted from CT image affected the classification performance due to variability in size and number of patches. The data enhancement although employing geometric transformation can make the dataset larger, it cannot provide images of various lesions. Only patterns existing in the original images from which they were generated will appear in the synthesized lesion images, hence some of the researcher used both geometric transformation and deep learning GAN model to generate synthesized images. To overcome the limitation of different approach to deal with limited data set, some of the research uses hybrid technique which gives quite better performance.

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