

Estimation of Level of Liver Damage Due to Cancer using Deep Convolutional Neural Network in CT images



Swapnil V. Vanmore, Sangeeta R. Chougule

Abstract: The lesion size estimation is essential need while diagnosing the liver cancer and treatment scenario. The lesion segmentation using conventional methods such as region growing, threshold based segmentation provide limited performance due to variations in light intensity distribution throughout the image. The deep learning approach used in this paper consist of input dataset of liver abdominal images along with labelled set combination of variety of liver regions and lesion structures. The care has been taken while constructing the dataset such that, the lesion due to cancer in liver of particular image should have at least one matching structure should be present in one of the labelled images. The 3 fold validation is done to evaluate the performance in which total 140 images of liver cancer are used for training, 30 images for validation and 30 images for testing. The result shows 98.5% accuracy for lesion classification. The area of lesion is compared to total area of liver in terms of pixels to estimate the total area occupied by the lesion and amount of liver damage.

Index Terms: Liver cancer, medical image segmentation, neural network, lesion segmentation, deep learning.

I. INTRODUCTION

Liver cancer is most important disease considered which causes maximum deaths out of total number of deaths in the world due to cancer disease. The liver cancer detection using manual methods is thus to be assisted using automated processes to boost the speed of detection. Image processing based diagnosis for liver cancer lesion detection have triggered the research requirements for such applications. The lesion segmentation using conventional segmentation methods such as region growing, threshold based methods show limitation in terms of applicability when there are changes in CT image contrast information along with irregular shows of lesions. It is impossible to predict the shape of lesion and hence there is need to have neural network based approach which could provide solution for the need.

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Image ROI segmentation using deep learning is almost required process in many medical image processing applications. The deep learning using encoder decoder method provides sufficiently good processing speed along with good results due to less complex network formation during training phase.

In this paper, the method for lesion ROI segmentation and estimation of lesion area versus total liver area is estimated for total liver damage analysis.

The paper further is organized in which second section focuses on related work in the field, section three shows the proposed work and methodology followed by results and analysis in section four. Finally, we conclude the method proposed in this paper which is followed by references.

II. PROCEDURE FOR PAPER SUBMISSION

A tumor segmentation challenges for liver tumor since 2008 gave rise to development of variety of methods [2]. Häme et al [3] shown the method of fuzzy based clustering approach for tumor segmentation. Massoptier et al [4] have shown method of tumor segmentation which uses K-means clustering. Based on this lesion regions are extracted. Shimizu et al [5] have given method which uses AdaBoost classifier by training the feature set. This handcrafted method provides label discrimination. Zhou et al [6], have a method of semi-automatic segmentation. The method makes use of support vector machine (SVM) classifier. The tumor regions are extracted in iterative processing manner. In paper [7], a method of clustering using Random forest (RF) is used for brain tumor segmentation application.

These methods were totally handcrafted methods which specifically depend on application problems to be solved in segmentation processing. Based on many methods available, the neural network based deep learning approach can provide sufficiently good results over handcrafted regions. The convolutional neural network based implementations can obtain outstanding performance on such challenging tasks of segmentation [8] and image classification [9]. One of the application for knee cartilage segmentation is shown in [10]. The supervised learning method using deep CNNs is given by LeCun et al. [11]. The model is formed by multiple layers neural networks.

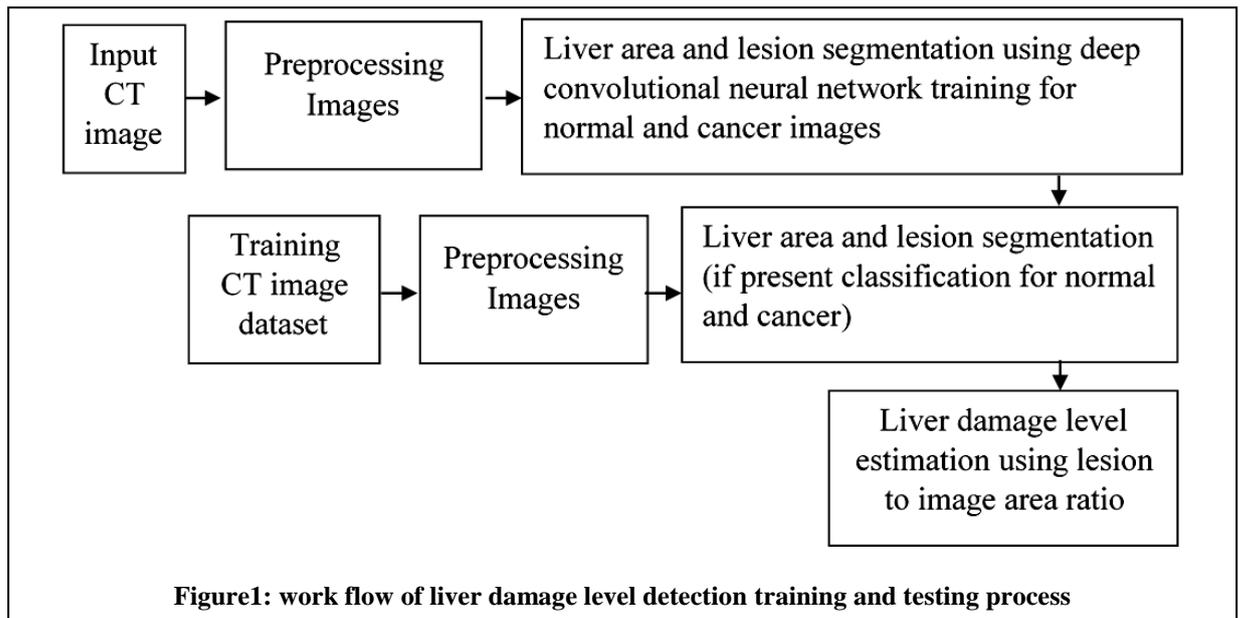
In this work, we aimed to use CNNs to describe liver damage level in CT images. The overall framework for training and testing process is showed in Figure 1.



The procedures include pre-processing, liver extraction, lesion segmentation, and classification and display the result of liver damage level based on lesion area to liver area ratio.

segmentation method

The selected liver region is then cropped in rectangle image



III. PROPOSED WORK:

Instead of focusing only on liver lesion patch as indicated in [3] affected by cancer, entire liver surface is considered for the sake of processing and detecting the level of liver damage using pixel level processing approach. The pixel level identification is considered with respect to number of pixels occupied by lesion area compared to total number of pixels in liver area. Figure 1 shows the processing algorithm for liver damage level detection stages involved in this research work.

Abdominal CT images are taken as input and preprocessed using Gaussian filter to remove the noise and then Weiner filter is used to increase the sharpness level of the image. The liver area segmentation process from abdominal CT image, is done using intensity of pixel based process. For this, we have used traditional level set based region growing method, for detecting the liver regions.

In region growing based segmentation, instead of manual seed point selection process for region growing, we have set the particular seed point by considering mean position for starting point of the region by trial and experiment method. The exact liver region identified by region growing is as shown in figure 2. The growing pattern of the region growing technique varies from image to image. This can be corrected by histogram equalization method for all images which achieves light intensity distribution in entire image to uniform level thereby accurate segmentation of liver area using manual segmentation method.

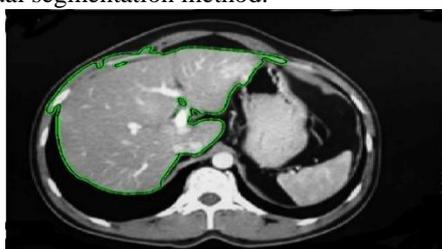


Figure 2: Liver area segmentation using manual

using rectangle derived from minimum and maximum values of x and y coordinates of the highlighted liver region. This leads to getting only liver region in the image thereby removing unnecessary organs being present in CT image and thereby preventing the degradation of the performance of the entire system. The cropped image is as shown in figure 3. After cropping the binary mask is developed to mask the regions outside liver area. The binary mask is as shown in figure 4. The true region is then used to extract contents from the main image. The resulting liver only image is as shown in figure 5.

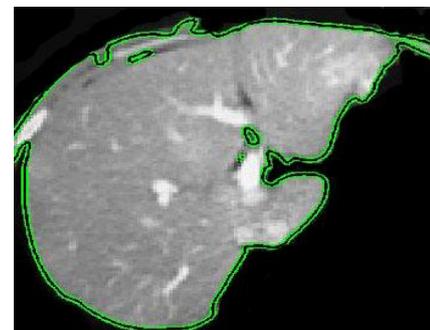


Figure 3: cropped liver image

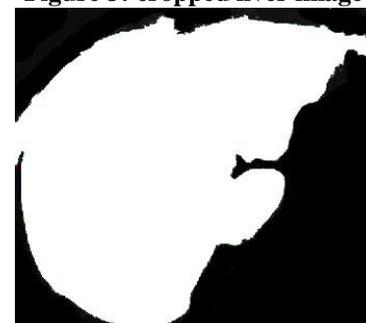


Figure 4: binary mask of liver region as per ROI from region growing

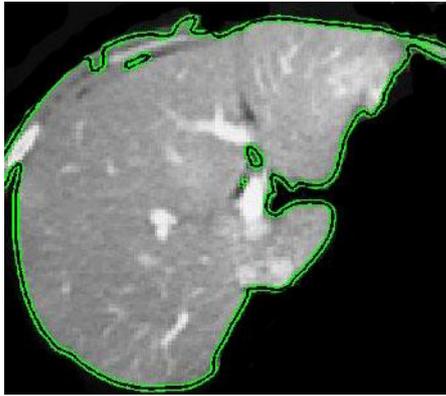


Figure 5: Liver only image extracted from main image using binary mask

The liver obtained in figure 5 can be used to extract the pixels inside liver region. The pixels in liver region are taken into consideration with respect to binary mask as Boolean values and only true liver pixels are used to process in Deep CNN. While extracting the lesion region a similar approach is used. The set of labelled mask images are used which consist of various combinations of lesion structure types. Figure 6 shows the mask obtained for the lesion for another liver image. Figure 6 shows the identified region of lesion.

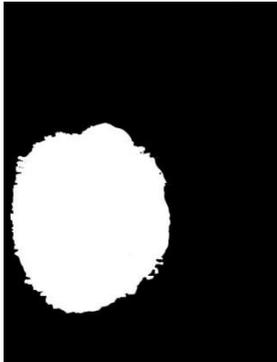


Figure 6: Lesion region binary mask

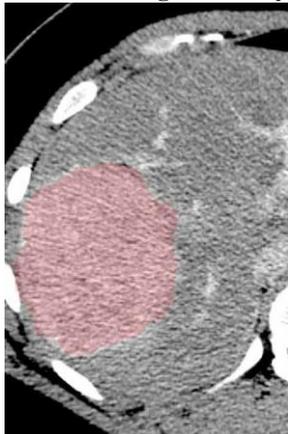


Figure 7: lesion region identified in the liver

The partial network architecture can be visualized as shows in figure 8 which consist of stack of encoder and decoder layers. The estimated number of layers in this work shows use of layers of encoding and decoding in which every next layer uses sampling rate of half of the previous layer. It has been observed that, effect of rotation and scale variations are not considerable as because, input abdominal CT images are having consistent scale and orientation.

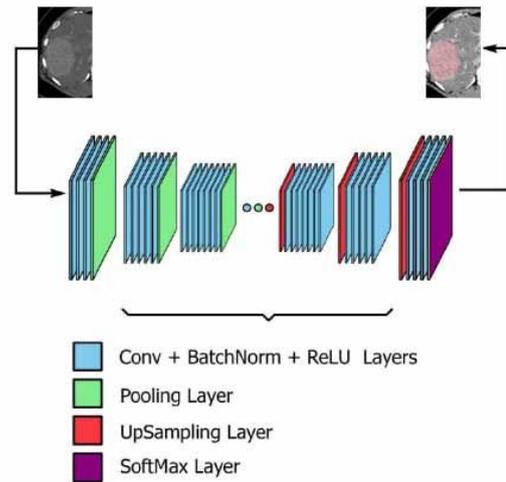


Figure 8: Layered architecture of deep CNN used in experimentation

In this work, ReLU is used as nonlinear activation function with max-pooling subsampling in encoder and up sampling in decoder stages. The respective layered structure of encoder and decoder is used for sampling and total number of filters used are 64 which is kept constant in throughout processing. This way unpooling of layer problem is solved. The soft-max function is used at the final stage layer to get the respective output.

True positive (TP), true negative (TN), false positive (FP), false negative (FN) parameters are considered for performance evaluation. When pixels from image belong to cancer area and are detected in that area are considered as TP, when pixels belong to cancer area but detection does not contain that pixel then it is considered as TN, in similar fashion when non lesion region pixel is detected as lesion region pixel it is FP and when it is detected as non lesion region pixel it is FN. The dice similarity coefficient (DSC) is estimated as,

$$DSC = \frac{2TP}{FP + 2TP + FN} \dots(1)$$

The DSC is unit-less and it is 100% when region is perfectly segmented with respect to ground truth mask and it is 0% when no region is detected compared to existence in ground truth mask.

Recall and precision are used to estimate the proportion of reference within segmentation and proportion of segmentation within reference respectively. The estimation is done using equations

Recall =

$$Recall = \frac{TP}{TP + FN} \dots(2)$$

$$Precision = \frac{TP}{TP + FP} \dots(3)$$

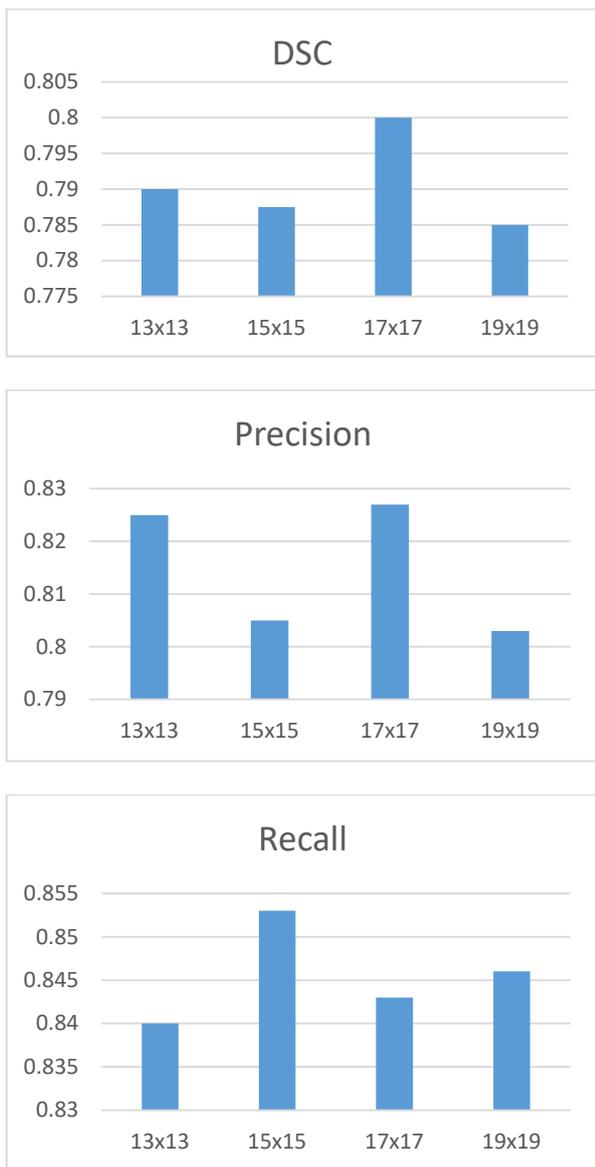


Figure 6: Performance evaluation of the proposed system Comparative method:

The proposed system is modified and implemented using multiclass SVM instead of Deep CNNs and the results are compared with our approach to check the effective improvement of deep learning approach.

The comparative provides study of machine learning as classifier along with conventional feature extraction procedure versus deep learning based feature extraction and classification for segmentation application of liver CT images.

Table 1: comparative analysis of Deep CNN and SVM based methods.

Method	DSC(%)	Precision(%)	Recall(%)
Proposed method	78.5	83.67	84.34
Comparative method using SVM as classifier	80.06	81.26	82.06

IV. CONCLUSION

In this paper a new, practical application of CNNs was presented to estimate liver damage due to cancer. This

method was tested on 200 CT images out of which 140 were used for training, 30 were used for validation and 30 were used for testing in 70:15:15 ratio. The experiments demonstrated that the CNNs model produced accurate and robust liver damage level detection. Compared to traditional machine learning method such as SVM, the CNNs method performed better. The CNNs still has limitation on producing results with inhomogeneous density of liver images and unclear intensity variational maps as cancer has variety of effective shading patterns on affected regions of liver.

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