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Double Stage Guassian Filtering and Marker Controlled Watershed Transform based Deep Learning Technique to automatically Detect Liver Cancer Using CT Scan Images

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Abstract: According to a survey conducted by Globocon 2020, Liver Cancer was the sixth biggest reason of death globally due to deaths caused by cancer. Another survey concluded that early detection of liver cancer increases survival rate of persons suffering from cancer. Traditional methods are not as fast and conclusive, Hence we propose a Computer Aided Diagnosis(CAD) method for early detection and treatment of liver cancer. Proposed method is based on Double Stage Guassian Filtering and Marker Controlled Watershed Transform based Deep Learning Technique. It is a two step process where pre-processing and segmentation is performed in first step and classification is performed in next step. 200 clinical and 200 secondary data from LiTs data set was used to train, test and validate our model. Proposed model achieved 96.42 % accuracy for primary dataset and 96.66 % accuracy for secondary data set. Our model is ready to be tested on bigger dataset and can be deployed at imaging centres in near future..

***Keywords**: DCNN Model, Liver Cancer, Marker Controlled Watershed transform, Double stage Guassian Filter*

1. Introduction

Liver is an organ located at the right upper side of stomach, surrounded by kidney, lungs, intestines, and pancreas[1]. The primary function of liver includes filtering the blood coming from digestive track and re-distribute it to rest of the body[2]. It helps in detoxification of chemicals, bile secretion, and production of protein for blood clotting.

Liver cancer is generally diagnosed in males and aged people. Clinically, liver cancer is diagnosed by analyzing the level of alpha-fetoprotein and bilirubin enzymes in blood, along with liver biopsy. In the last decade various manual tests have been adopted to diagnose the liver cancer such as immunotherapy, Oncolytic Virus Therapy, and Cytotoxic Chemotherapy [3]. However, manual liver cancer detection is expensive, time consuming, and prone to inaccuracies. Therefore, computer-aided liver cancer detection is always required.

Computer-aided liver cancer detection is a exigent task because of the size, shape, and placement of liver within the human anatomy. Cancer detection is usually carried out in two steps: In first step, medical images are used to segment the liver from other organs. In second step, cancerous cells are detected from the segmented image [4]. In the literature, various approaches and algorithms for liver cancer detection have been proposed and implemented [5]–[7]. It has been observed from the literature that there is a vast scope of further research towards liver cancer detection.

Recent works have effectively used DCNN-based deep learning techniques to address a variety of issues [8]. Deep Convolutional neural networks (DCNN) were successfully applied in automatic technique to segment afflicted lesions in CT images, achieving a dice similarity (DS) coefficient of 80.06% [9]. A deep learning system with graph cut refinement was created by Lu et al. [10] to automatically and effectively segment the CT scans. Deep learning method for classifying liver disorders was published by Kaizhi et al. [11]. Hu et al. [12] examined deep learning methods for cancer detection and diagnosis, including deep convolutional neural networks, fully connected neural networks and deep belief networks. In this Paper we have presented an automated technique to detect liver cancer from CT scan images using Deep Convolutional Neural Networks.

2. Methods

We Propose a Computer Aided Diagnosis (CAD) based model called Double Stage Guassian Filtering and Marker Controlled Watershed Transform based Deep

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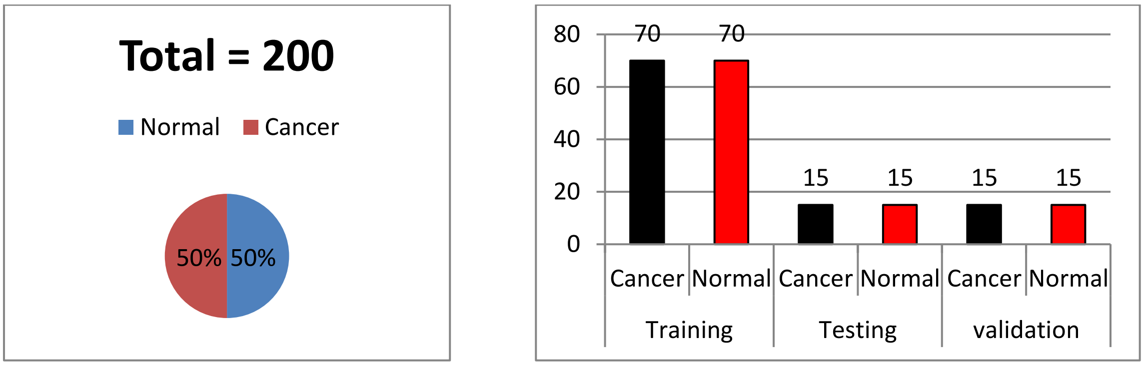
Learning Technique, which consist of efficient pre-processing of liver CT images, effective segmentation of images to obtain Region of Interest(ROI), and finally using pre-processed and segmented image to classify the image into normal or cancer images. The proposed workflow is illustrated below in Fig. 3. Double stage guassian filtering, Contrast Limited Adaptive Histogram Equalization and Median Filter Technique is applied to pre-process the image. Post Pre-processing Otsu's thresholding, Distance transform and marker controlled watershed algorithm is applied for segmentation. Segmented image is referred as the enhanced image which contains ROI. Finally the extracted image is classified with the help of Deep Convolutional Neural Network into normal or cancer image.

2.1. Data Set

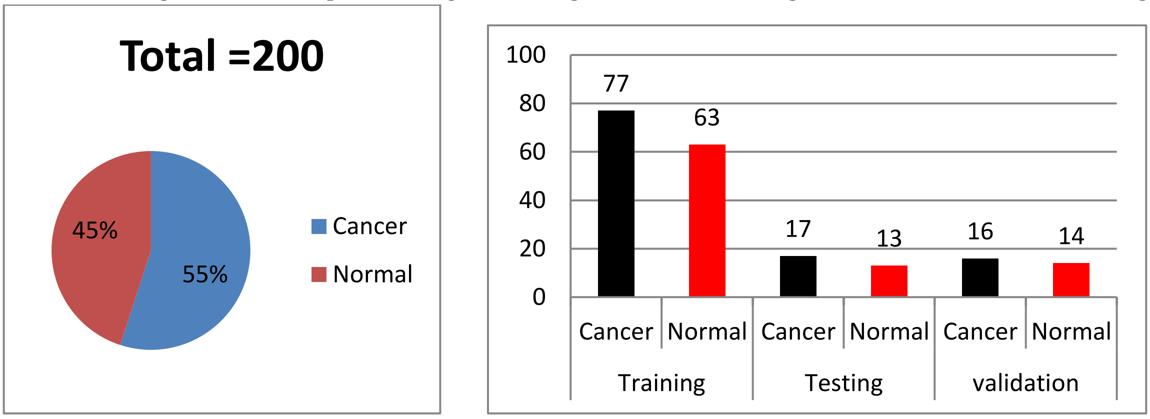
Proposed was trained and tested on two sets of data. Primary Data Set was obtained from the imaging centre of Life Line Multi Speciality hospital, Nagpur. A total of 200 images was obtained containing 100 images of both normal and cancer patients. Images of both male and female and of all ages was obtained. these images were divided into training,testing and validation images as shown in Fig. below.



(a) (b)

Fig. 1a) Distribution of Primary dataset. 1b) Data split into training, testing and validation

Lits Dataset is used as secondary dataset. Lits Data set also consist of 200 Liver CT images having 110 cancer images and 90 normal liver images. The breakup of training and testing and validation images of Lits dataset is shown in Fig. below.



(a) (b)

Fig. 2a) Distribution of Secondary dataset. 2b) Data split into training, testing and validation

Primary images were recorded on GE Medical Imaging Device and the images are having thickness of 0 .5 mm and resolution of images are 512 X 512. The study was performed on Google colab on personal system having Windows 10, Intel core i5 64 bit processor having 8 GB RAM.

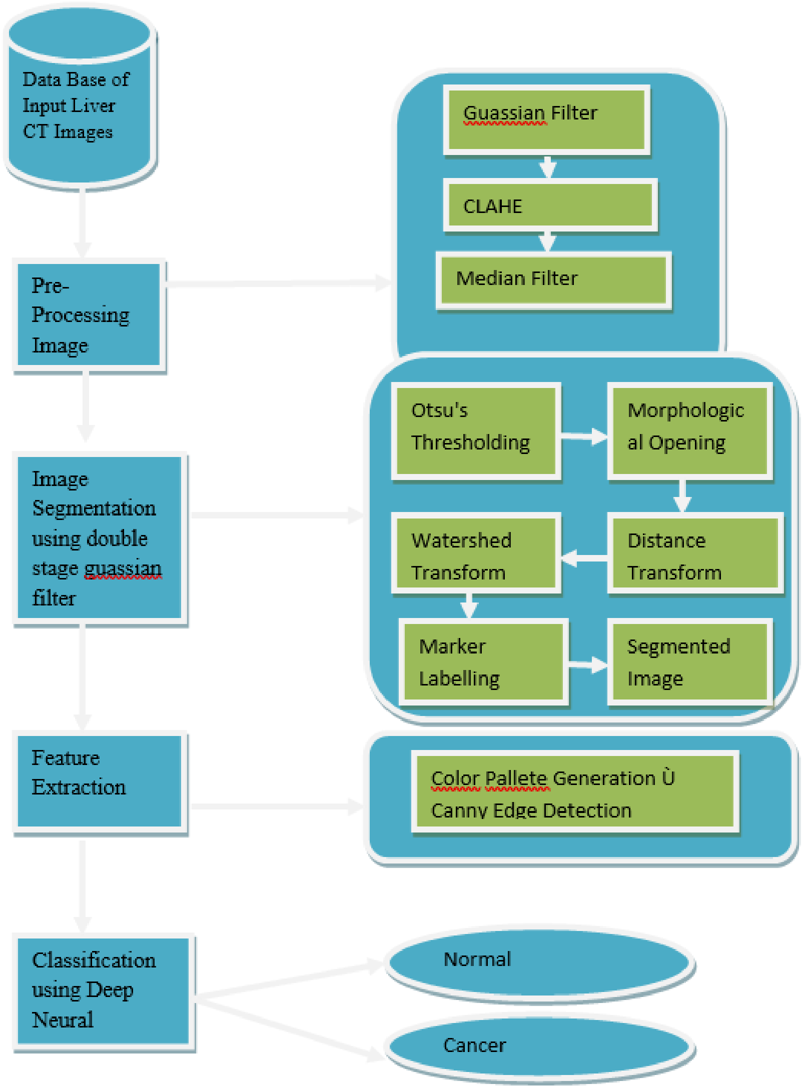


Fig. 3. Workflow of the Proposed CAD Model

2.2 Guassian Filter

Guassian Filter is used in image processing to reduce noise and also preserving the edges and other details of image[13]. Guassian filter is normally implemented as an odd sized symmetric kernel such 3x3, or 5x5 or 7x7. A guassian filter has certain advantages over other filters like it is completely fair and its fourier transform is also a guassian distribution centered around the zero frequency[14].

2.3 Contrast Limited Adaptive Histogram Equalization (CLAHE)

This technique is very effective in smoothing out an image. It may sometimes happen that the pixels of an image are either very bright or very dark. This may result in loss of desired area to be segmented. To smooth out the image Histogram Equalization is used in many forms. In CLAHE the image is divided into several sections and several histograms are computed corresponding to each section. These histograms are then used to redistribute the brightness of the image.

2.4 Median Filter

Median Filters are best suited for removing salt and pepper type of noise from images[15]. Median filter is a non linear filter, which works by navigating on each pixel of the image and the value of a pixel with the mean value of its neighbouring pixels.

2.5 Otsu's Thresholding

Otsu's thresholding is used for foreground and background estimation of an image[16]. in simple words, it calculates the variance of an image that separates the foreground and background of an image and returns the threshold value that separates both[17]. This threshold value can then be used to separate the foreground or background of an image as desired.

2.6 Marker Controlled Watershed algorithm

Watershed algorithm is a region growing algorithm that is used to segment multiple objects in an image[18]. This algorithm requires a that at least one marker or seed point be selected inside an image. This can be selected randomly or based on some knowledge or calculation[19]. The nearby pixels are than added and the region grows. Watershed considers the image as mountain tops and valleys[20]. The bright pixels are considered as mountain top and the darker pixels are considered as valleys. The water is then flown from top, which starts filling the valley. the boundary of an object works as the walls of the dam which prevents the water from different valleys to mix together[21]. These areas are then represented with different colours that indicates different objects in an image.

2.7 Feature Extraction

In computer graphics, colour quantization is applied to colour spaces[22]. It's job is to lower the number of distinct colours used in an image, with the aim of making new image look as similar to the original as possible. Next step is to extract the colour pallet from converted bitmap image to understand the different colour shades in the image[23]. This is most important step as it output the percentage of different colour level with colour code in the image. Now these colour codes further utilized by flood fill algorithm and segmentation algorithm for accurate segmentation. System need to process the edge detection algorithm to in order to enhance segmentation process accuracy. Before segmentation to take place, system need right edges from the image. Based on the boundary and the differences in the colour level or colour shades system detects the area or segment the area in image

2.8 Deep Convolutional Neural Network(DCNN)

DCNN are one of the most popular artificial neural network used in medical image processing. What makes DCNN so popular is that the fact that they are capable of finding out hidden patterns and make sense out of it[24]. It is this special ability that makes DCNN extremely useful for classification of medical images.

A typical DCNN consist of an Input Layer, number of hidden layers which are combination and sequence of convolution layer, ReLu and Pooling layers and Output Layer[25-28]. Some DCNN have also a fully connected layer just before a output layer. A convolution layer accepts input, transforms it and gives it as output. This operation is called convolution operation. Convolution Layer is responsible for finding out important features of an image.

Pooling layers reduce the dimensions of an image with losing any valuable information from the image. This helps in reducing the number of parameters to be found and ultimately the amount of processing in the network. There are many pooling functions, but max pooling is the most popular function used in DCNN[29].

Table 1. Details of parameters tuned in proposed model

Model Used	Sequential
Input Activation function	ReLU
Output Activation function	Sigmoid
Optimizer	Adam
Epoch	220
Batch	15
Learning Rate	.001
Loss Function	Binary Cross Entropy
Metrics	Accuracy
Validation Split	0.2

2.9 Evaluation Parameters

Performance for pre-processing was evaluated in terms of Mean Square Error(MSE), Structural Similarity Index Metrics(SSIM) and Peak Signal to Noise Ration(PSNR). Segmentation performance was evaluated in terms of Dice Score(DS), Volume Overlapping Error (VOE), Relative Volume Difference (RVD) and Jaccard Index(JI). Classification performance is measured in terms of Accuracy, Sensitivity, Specificity, F1 Score and Precision. Equations of all the above-mentioned parameters are as follows,

$$\mathrm{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - k(i,j)]$$

$$\mathrm{SSIM}(x,y) = \frac{(2\mu x\mu y+c1)(2\sigma xy+c2)}{(\mu x^2+\mu y^2+c1)(\sigma x^2+\sigma y^2+c2)}$$

$$\mathrm{PSNR} = 10\log10\left(\frac{2^b-1}{\mathrm{MSE}}\right)$$

$$\mathrm{DS}(\mathrm{BM},\mathrm{GT}) = \frac{2|\mathrm{BM}\cap\mathrm{GT}|}{|\mathrm{BM}|+|\mathrm{GT}|}$$

$$VOE\ (BM,GT) = 1-\frac{|BM\cap GT|}{|\mathrm{BM\ U\ GT}|}$$

$$RVD\ (BM,GT) = \frac{|BM|-|GT|}{|\mathrm{GT}|}$$

$$\mathrm{JI\ (BM,GT)} = \frac{\mathrm{DS}}{2-\mathrm{DS}}$$

ACCURACY = $(TN + TP) / (TN + TP + FN + FP)$

PRECISION = $TP / (TP + FP)$

SENSITIVITY = $TP / (TP + FN)$

SPECIFICITY = $TN / (TN + FP)$

where Base Mask (BM), Ground Truth (GT), True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN).

3. Experimental Results

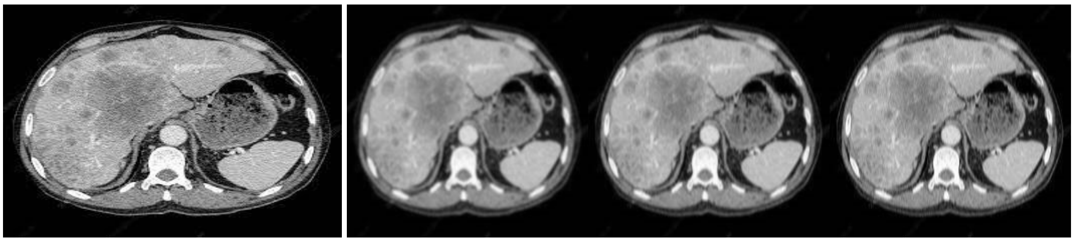
Proposed CAD model was tested on both primary and secondary data. Primary data consist of 200 Liver CT images and Secondary data also consist of 200 liver CT images. Both data set consist of images of varied contrast levels, tissue abnormalities, liver size, age and gender. Liver cancer detection is a two step process: In first step the image is pre- processed and segmented to obtain Region of interest and in the segmented features are extracted to classify the image as cancer image or normal image. Fig. Shows the complete steps of pre-processing and segmentation. Fig. shows the process of abnormality estimation and classification.

Fig. 4a to 4e presents the result of pre-processing. Original CT images are pre-processed to remove noise from them. Pre-processing performance is measured using MSE, SSIM and PSNR. Values are calculated as per above mentioned formulas. MSE and PSNR values close to 1 and PSNR value between 50-60 indicates good results of pre-processing. Table 2. presents the experimental results of proposed method for primary and secondary data set.

Fig. 5a to 5f presents the segmentation results of proposed method. Pre-processed images are used as input to segment CT image in order to obtain Region of Interest. To check the performance of segmentation, segmented image is compared with Ground Truth image using DS, RVD, VOE, and JI using above mentioned formulas. Table 3. presents the experimental results for segmentation. RVD value close to 1 and DS, VOE and JI close to 0 indicates better segmentation results.

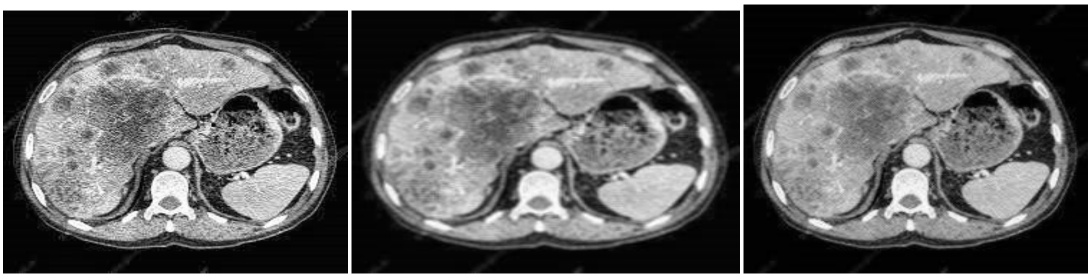
Fig. 6a. to 6d. presents experimental results of classification. Features are extracted from segmented images to create a library of images that is used to train, test and validate proposed model. Feature extraction is carried using colour palette generation, canny edge detection and abnormality clustering. Finally the abnormality clusters of all the images are used for abnormality matching in order to classify image as cancer or normal. Classification is performed using DCNN and performance of proposed model is measured using Accuracy, Sensitivity, Specificity and precision as evaluation metrics. Table 4 to Table 7 presents the experimental findings of proposed system on both primary and secondary data set.

Orignal Image Double Stage Guassian Smoothed Image



(a) (b)

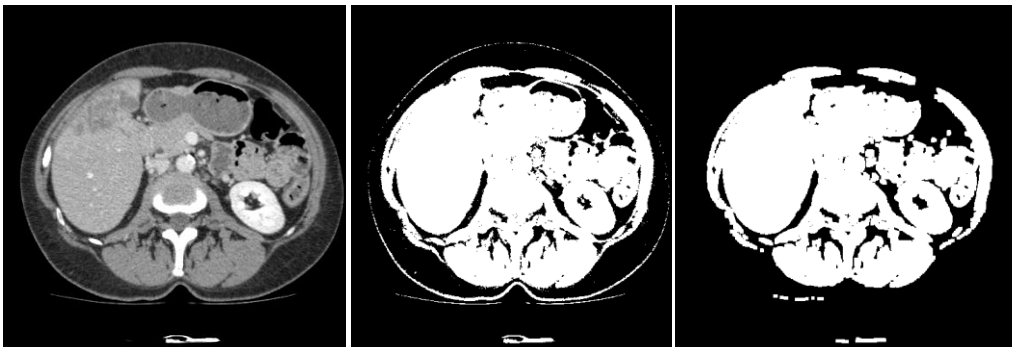
CLAHE Median Filtered Pre-Processed Image



(c) (d) (e)

Fig. 4. Pre-Processing results a) original image b) Double stage guassian filtered image c) Adaptive histogram applied image d) Median filter applied to remove salt and pepper noise e) pre-Processed image

Pre-Processed Image Otsu's Thresholding Distance Transformed



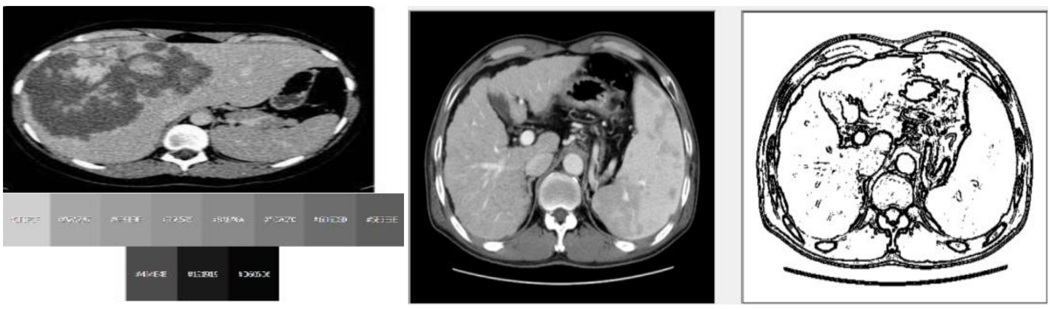
(a) (b) (c)

Watershed Transform Segmented Image Ground Truth

(d) (e) (f)

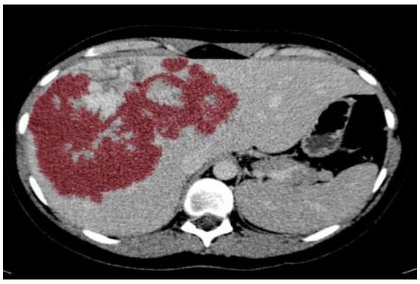
Fig. 5. a) Pre-Processed image from previous stage b) Otsu's Thresholding applied for foreground estimation c) Morphological distance transform applied d) Marker controlled watershed to segment liver e) Segmented image or Region of interest (ROI) f) Ground Truth image to validate result

Color Pallette Canny Edge Detection



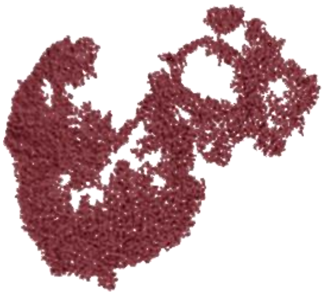
(a) (b)

Abnormality Estimation



(c)

Cluster Separation



(d)

Fig. 6. a) Colour Palette Generation b) Canny Edge Detection for boundary estimation c) Abnormality Clustering d) Abnormality separation for classification

Table 2. Pre-Pre-Processing result for Primary and Secondary Dataset

Data Used	**Primary Set**			**Secondary Set**		
Method	**MSE**	**SSIM**	**PSNR**	**MSE**	**SSIM**	**PSNR**
Proposed Method	**0.85**	**55.56**	**0.88**	**0.84**	**54.5**	**0.86**

Table 3. Segmentation Result for Primary and Secondary data of Proposed Model

Dataset	DS	RVD	VOE	JI
Primary	**.94**	**.235**	**.935**	**.095**
Secondary	**.98**	**.126**	**.964**	**.08**

Table 4. Confusion Matrix of proposed model for Primary Dataset

Training Set			**Testing Set**			**Validation**		
Class	**Cancer**	**Normal**	**Class**	**Cancer**	**Normal**	**Class**	**Cancer**	**Normal**
Cancer	**69**	**1**	**Cancer**	**14**	**1**	**Cancer**	**15**	**0**
Normal	**4**	**66**	**Normal**	**2**	**13**	**Normal**	**1**	**14**

Table 5. Confusion Matrix of proposed model for Secondary dataset

Training Set			**Testing Set**			**Validation**		
Class	**Cancer**	**Normal**	**Class**	**Cancer**	**Normal**	**Class**	**Cancer**	**Normal**
Cancer	**75**	**2**	**Cancer**	**16**	**1**	**Cancer**	**15**	**1**
Normal	**3**	**60**	**Normal**	**2**	**11**	**Normal**	**2**	**12**

Table 6. Obtained results from our proposed DCNN Model for Primary Data Set

Parameters	Training (%)	Testing (%)	Validation (%)
Accuracy	**96.42**	**90**	**96.66**
Sensitivity	**97.1**	**93.33**	**100**
Specificity	**94.28**	**92.8**	**93.33**
Precision	**94.5**	**87.5**	**93.75**

Table 7. Obtained results from our proposed DCNN Model for Primary Data Set

Parameters	Training (%)	Testing (%)	Validation (%)
Accuracy	**96.42**	**90**	**90**
Sensitivity	**97.4**	**88.88**	**93.75**
Specificity	**95.23**	**84.61**	**85.71**
Precision	**96.1**	**88.88**	**88.23**

4. Conclusion

In this paper, we have proposed a CAD method to pre-process , segment and classify CT images in order to quickly detect Liver Cancer. Early Detection is crucial in the treatment of cancer and survival of patients. Proposed method is trained and tested on both clinical and secondary data and have achieved significantly high accuracy levels of 96.42% on both the data sets. Proposed model is also validated on real clinical images and have achieved a high accuracy of 96.66%. Proposed model is based on DCNN and is effective in early detection of liver cancer. In future, proposed model can be used by Experts to segment and detect liver tumour for effective treatment and medication.

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