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Feed Forward Neural Network Based Automatic Detection of Liver in Computer Tomography Images

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Abstract : Liver detection in CT/MR images is vital, because it is the preliminary task before diagnosing liver diseases like liver tumor and liver transplantation. This paper presents a neural network based model for the automatic detection of liver in CT images. As the input CT image contains noise incurred during the acquisition, the image is pre-processed with decision based median filter. Local features are extracted using first order statistics and texture features are extracted by gray level co-occurrence matrix. The back propagation neural network is used for the classification of pixels into liver and non-liver regions. The features are normalized and training comprises of inputs from seven data sets. The tumor boundary detection was done by localized region based active contour model. The proposed algorithm was tested on real time CT images and evaluated both qualitatively and quantitatively.
Keywords : Neural Network, Segmentation, noise, local features, texture.

1. Introduction:

In medical imaging context segmentation is a process of partitioning an image domain into non-overlapping connected regions that correspond to significant anatomical structures. Medical imaging techniques such as computer tomography (CT), Magnetic resonance imaging (MRI) have revolutionized the modern medicine and the segmentation of abdominal organs like liver and kidney is an important step in many diagnostic and surgical procedures. The CT images, in general are corrupted by Gaussian noise, salt and pepper noise and MR images in general are corrupted by rician noise[1]. An appropriate pre-processing is needed prior to segmentation and there is no universal algorithm for segmentation. The choice of segmentation algorithm depends upon the application.

A Markov random field model was developed for the segmentation of liver from Abdomen CT images in which the result was refined by gradient vector field and active contour[2]. The region growing algorithm along with the morphological operation was developed for the segmentation of the liver form CT images and the tumor regions were extracted by alternative Fuzzy C-Means algorithm[3]. A semi-automatic watershed segmentation model based on anatomical information along with morphological operation was proposed for the segmentation of liver lesions from CT images[4]. Neural network classifier based on feed forward neural architecture was used for the classification of liver anomalies (cyst, haemangioma, hepatocellular carcinoma)[5]. An approximate active contour model was developed by building polylines for the automatic segmentation of liver with and without lesions[6]. An advanced region growing algorithm based on statistical features was proposed for the segmentation of liver from CT images[7].The semi-automatic Bayesian segmentation model was developed for the extraction of liver from abdomen CT images[8]. An automatic iterative segmentation algorithm comprising of multilayer perceptron (MLP) with adjacent slice information was used for the segmentation of abdominal organs from CT images[9]. A 3D region growing algorithm with morphological operations was proposed for the segmentation of liver from CT images[10]. The SVM classifier based on local binary pattern features was used for the segmentation of liver with lesions[11]. A modified K-means hard clustering algorithm along with contour model was developed for the segmentation of liver from CT images and 3D rendering of liver region, volume calculation was done[12]. The artificial neural network has immense role in image processing and it plays a vital in medical image analysis especially in segmentation and classification[13]. The back propagation neural network is a commonly used feed forward neural network that dynamically alters the weight and bias values based on the error generated by comparing the actual output value and target output value[14].The Lankton algorithm is a localized region based active contour model and it evolves the initial contour based on the local neighbourhood statistics and can segment the image in to two homogeneous regions[15, 16]. This paper proposes a feed forward neural network for the detection of liver in CT images. The decision based median filter was used in the pre-processing stage and the segmentation result was refined by localized region based active contour model for tracing the boundary of tumor.Section 2 describes the materials and methods that comprises of acquisition protocol, pre-processing, feature extraction, neural network architecture, post processing. Section 3 describes the results and discussion and conclusions are drawn in section 4.

2. Materials and Methods:

2.1 Acquisition Protocol

The CT images have been acquired on Optima CT machine. Both plain and contrast enhanced CT images are taken with 0.6mm slice thickness. The patient consent was obtained for publishing the images. The abdominal CT images from 7 patients were collected in the data set. Each data set comprises of 150 to 200 slices and selective slices from each data set were used for analysis. The ethics committee for biomedical activities of Mar Ephraem International Center for Medical Image processing and Metro Scans & Laboratory, Thiruvananthapuram approved the study of CT images of human subjects for research work. The analysis was carried out on selective slices from each data set.

2.2Decision Based Median Filter

The median filter and Gaussian filter are widely used for the removal of Gaussian noise and impulse noise in many applications. But the median filter alters the non-noisy pixels and edge preservation is poor in Gaussian filter. In this paper the modification of median filter called decision based median filter is used for the noise removal in the pre-processing stage. The operation of decision based median filter comprises of two stages noise detection and noise removal.

Step 1: Choose a 2D window of size 3 X 3, Assume the processing pixel be X_{ij}

Step 2: Determine the minimum (X_{min}) and maximum (X_{max}) gray values of pixels in the processing window are computed

If $X_{min} < X_{ij} < X_{max}$, the pixel gray value ($X_{ij}$) is left unchanged, else move to the next step

Step 3: If $X_{ij} = X_{min}$ or $X_{ij} = X_{max}$, then the following condition is evaluated

When the neighbourhood pixel gray values in the mask are same as X_{ij} then it is a non-noisy pixel and is left unchanged, otherwise move to the next step.

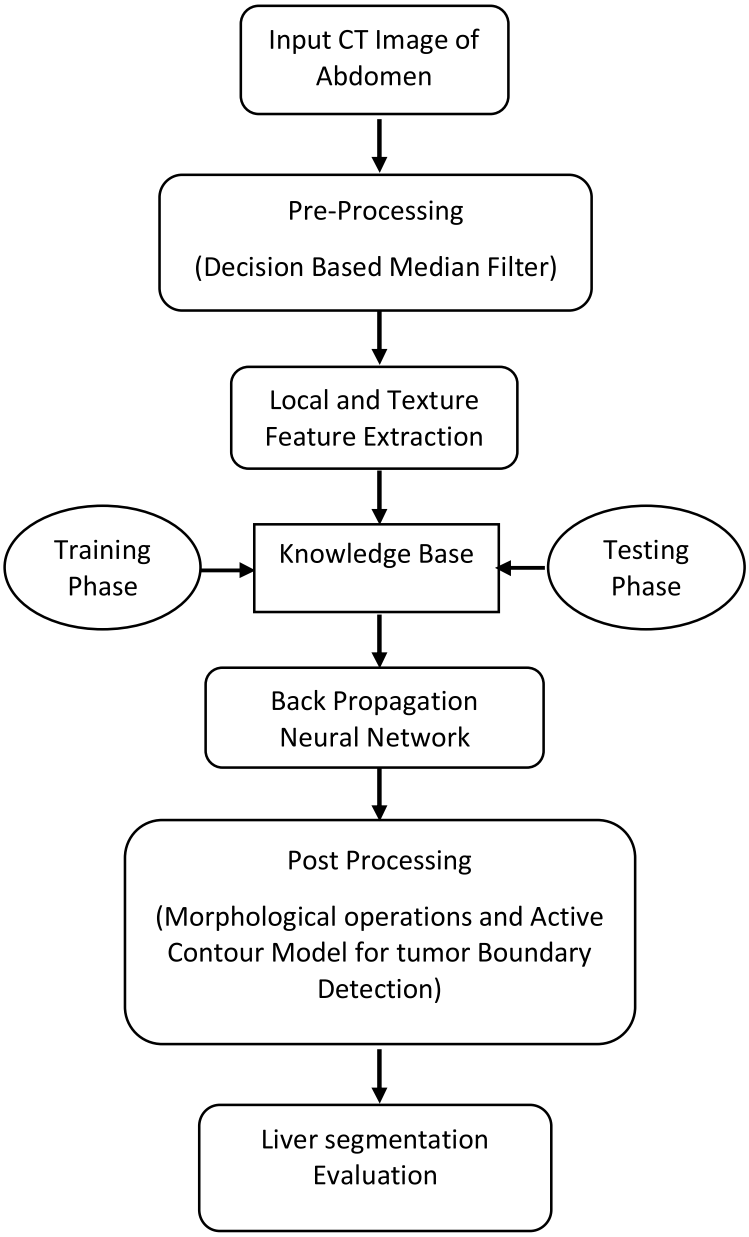

Figure 1: Block diagram of the proposed algorithm

Step 4: When X_{ij} is a corrupted pixel, there are two possible cases

Case i: Replace X_{ij} with the mean of the elements in the window, if the neighbourhoodpixelsgray value are X_{min} and X_{max}.

Case ii: Replace X_{ij} with the median value, when all the neighbourhood pixels grayvalue are not X_{min} and X_{max} , the median is determined from the elements in the window while discarding the pixels with gray value X_{min} and X_{max}.

Step 5: Repeat steps 1 to 4 until all the pixels in the image are processed.

The DBMF can thus efficiently remove the noise there by preserving the image details.

2.3 Feature Extraction

Local Features and Texture features are extracted for the segmentation of liver from CT images. The local feature include mean, variance, local minimum, local maximum, spatial feature of pixels and texture features such as contrast, correlation, energy and homogeneity. The texture features are determined from the gray level co-occurrence matrix (GLCM).The graycomatrix function in MATLAB is used to generate the GLCM matrix. The neural network is trained with the local and texture features for the segmentation of liver from the CT images. The local and texture features are normalized prior to training process.

2.4 Back Propagation Neural Network

The back propagation neural network is a supervised feed forward neural network type. The various stages of BPN algorithm are initialization of weights, back propagation of error and weight updation. In supervised neural network each input vector requires a target vector for classification. The input vector and target vector are presented during training phase. The actual output obtained in the testing phase is compared with the target output and error signal is generated. The weight updation is based on the error value and it is adjusted untilthere is a matching between the actual output and target output. The modification of weight is based on the gradient descent algorithm and the weights are modified when each training sample is presented to the neural network.

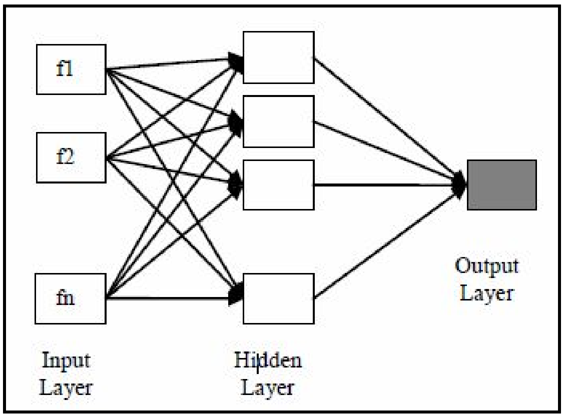

Figure 2: Feed forward back propagation neural network

The steps in back propagation algorithm can be summarized as follows

Step1: Initialize the weights

U_{ij} : Weights between input layer and hidden layer

V_{jk} : Weights between hidden layer and output layer

Step 2: For each training pair follow the steps 3-9. Each input unit receives the input signals (x_i) and transmits the signals to hidden layer units (z_j)

Step 3: Determine the response from hidden units. The hidden unit adds its weighted input signal and apply it to the activation function to compute the output signal

$$Zin_j = \Sigma x_i U_{ij} \quad (1)$$

$$Z_j = f\left(zin_j\right) \quad (2)$$

Step 4: Determine the response from output units. The output unit adds the weighted input signal and apply it to the activation function to compute the output signal

$$yin_k = \Sigma z_j V_{jk} \quad (3)$$

$$Y_k = f\left(yin_k\right) \quad (4)$$

Step 5: Determine the weight updation of the link connected to the output neurons

$$\Delta V_{jk} \quad \alpha e_k Z_j \qquad (5)$$

Where α is the learning rate, t_k is the target pattern and e_k is the error term

$$e_k = (t_k - y_k) f'(yin_k)$$

Step 6: Determine the weight updation of the link connected to the hidden layer neurons

$$\Delta U_{ij} \quad \alpha e_j Y_k \qquad (6)$$

Where $e_j = \Sigma e_k V_{jk} f'(zin_j)$

Step 7: Update the weight of the output layer unit

$$V_{jk}(new) = V_{jk}(old) + \Delta V_{jk} \qquad (7)$$

Update the weight of the hidden layer unit

$$U_{ij}(new) = U_{ij}(old) + \Delta U_{ij} \qquad (8)$$

Step 8: The training phase is terminated when the weight correction in (7) and (8) are equal to zero or a predefined value

2.5 Post Processing

The neural network response obtained in the previous stage is post processed to produce the actual segmented image. The morphological operations were performed and it is overlapped with the input image to produce actual segmented image. The input images along with the various stage results are depicted in the figure 5.The localized region basedlankton active contour model is used in the post segmentation stage to trace the boundary of liver tumor. Lankton active contour algorithm is a region based technique in which the contour evolution is determined by neighbourhood pixel statistical features. The lankton algorithm is based on the assumption that pixel features inside the initially drawn contour will have homogeneous characteristics when compared to the pixels outside the contour. The Creaseg software developed in Matlab was used for the tumor boundary detection[15].The efficiency of the neural network improves with the increase in number of inputs for training. The issues in global region based models like failing to detect the objects of low contrast and non-uniform illumination are overcome by local region based active contour models. The input images along with various stage results for liver with anomalies are depicted in figure 6.

3. Results and Discussion

In this work the liver regions are extracted automatically from the input abdomen CT images by the back propagation neural network. The input CT images are first pre-processed by decision based median filter prior to feature extraction. Seven real time abdomen CT data set were used for the analysis of liver segmentation. The 10 features are feed to the input layer of neural network. Hidden layer is the second layer and it comprises of 20 neurons. The output layer is the third layer and it consists of one neuron representing output. Each data set comprises of20 selective slices were used for training and the result of typical slice from each data set in the testing phase is depicted here. The three data set D1, D2 and D3 were used for the analysis of segmentation of liver. The next four data set D4, D5 D6 and D7 were used for the analysis of segmentation of liver with tumor. The data set D4 is a case of benign tumor (Haemangioma) and D5, D6, and D7 are the cases of malignant tumor (Hepatocellular Carcinoma). The proposed algorithm was thus tested on seven data set and the result of typical slices from each data set is depicted in figure 5 and figure 6. The performance of the segmentation result was evaluated in terms of similarity metrics such as dice coefficient (DC), rand index (RI). Also success & error rate metrics such as false positive volume fraction (FPVF), false negative volume fraction (FNVF) and true positive volume fraction (TPVF) are also used to evaluate the segmentation result.

Table 1: Performance metrics (%) for liver segmentation

Data Set	Slice details	FPVF	FNVF	TPVF
D1	S1	7.81	3.03	96.97
D2	S2	3.84	12.71	90.29
D1	S3	9.74	10.74	91.26
D3	S4	8.06	5.96	94.04
D1	S5	9.58	5.94	94.06
D4	S6	3.29	5.96	94.02
D5	S7	3.31	10.23	88.77
D6	S8	3.64	9.56	94.35
D7	S9	3.87	13.28	94.67

The computation of above said metrics requires ground truth image which was generated by an expert physician (radiologist) by carefully tracing the region of interest in the medical image. The table 1 represents the success and error rate in percentage for typical slice corresponding to the data set. The FNVF and FPVF are the measure of misclassifications occurred at inside the liver and outside the liver. The TPVF measures the similarity of classification between machine generated result and gold standard image. The FNVF and FPVF rate should be low and TPVF should be high for an efficient segmentation algorithm. The dice coefficient is a measure of spatial overlap between segmented image and gold standard image. Their values ranges between 0 (no overlap) and 1 (perfect matching).

The dice coefficient (DC) is represented as follows

$$DC = \frac{2|TP|}{2|TP| + |FN| + |FP|} \quad (9)$$

The rand index evaluates the consistency of pixels in the segmented and ground truth image. The value of rand index ranges from 0 to 1. The value '0' indicates the dissimilarity between segmentation result and ground truth image. The value of '1' indicates the perfect similarity between segmentation result and ground truth image.

The rand index (RI) is represented as follows

$$RI = \frac{|TP| + |TN|}{|TP| + |FN| + |TN| + |FP|} \quad (10)$$

Where TP, FN, FP, TN are the true positive, false negative, false positive and true negative values.

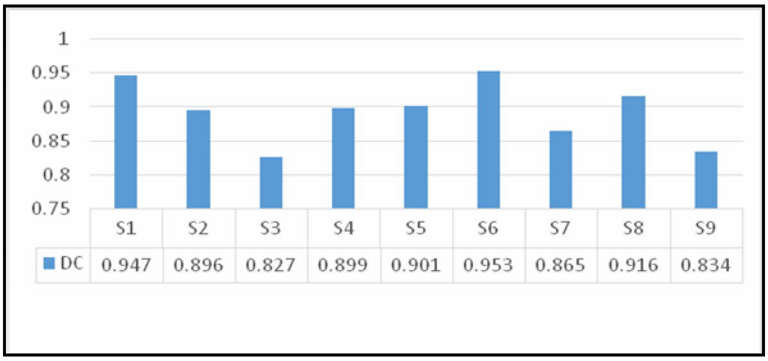

Figure 3: Dice Coefficient Plot for liver segmentation

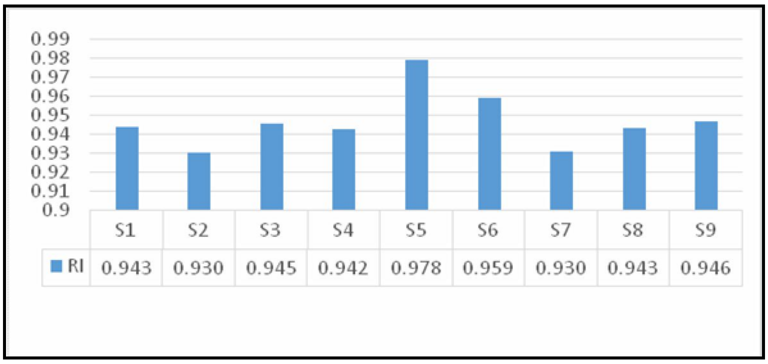

Figure 4: Rand Index Plot for liver segmentation

The success and error rate value in table 1 indicates the efficiency of the proposed algorithm. The value of DC and RI in figure 3 and 4 is nearby 1 that also indicates the efficiency of the proposed algorithm.

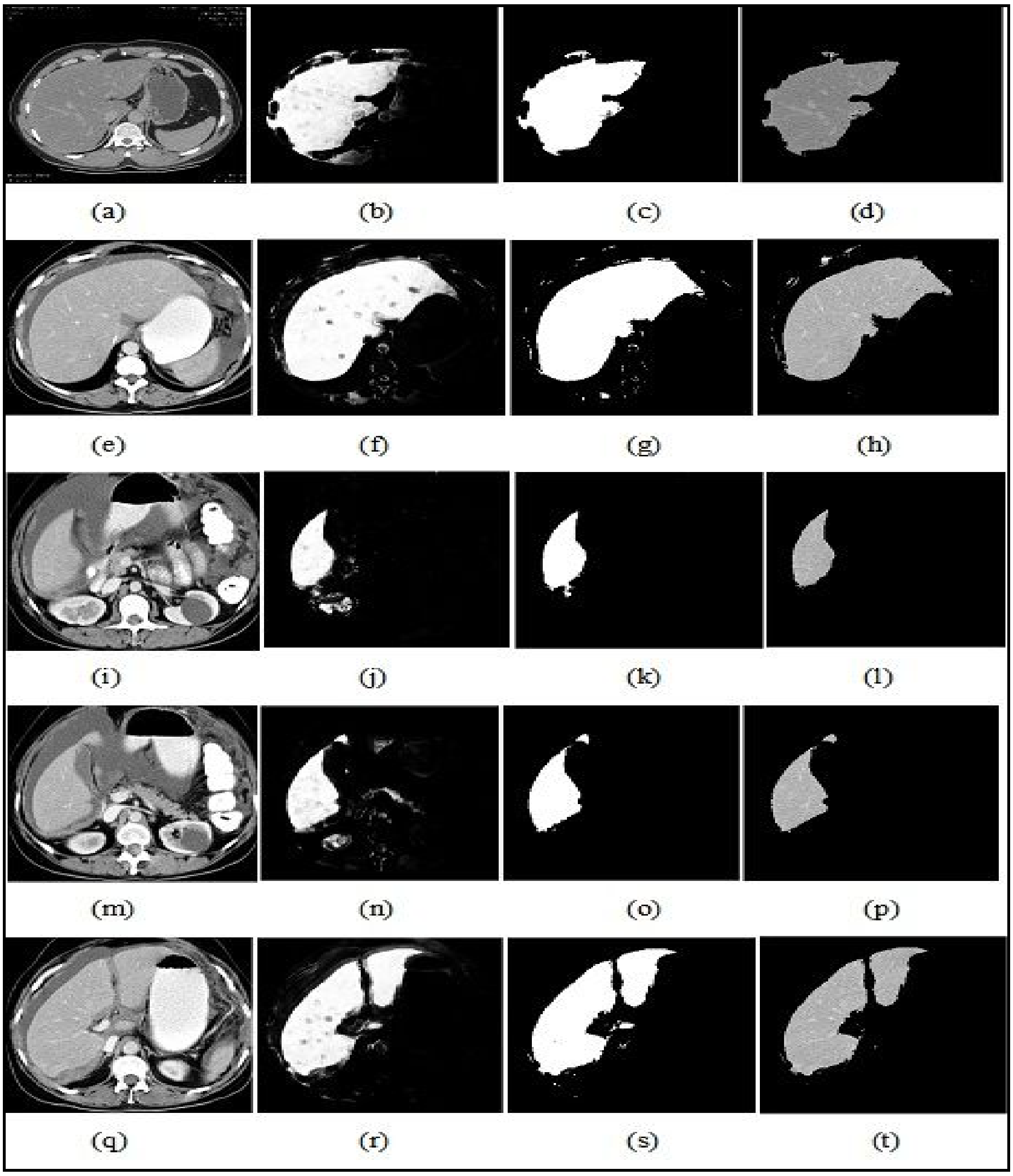

Figure 5 : (a (S1),e (S2),i(S3),m(S4),q (S5)) Pre-processed images , (b.f,j,n,r) Neural network response , (c,g,k,o,s) Post processed images , (d,h,l,p,t) Final liver segmentation output

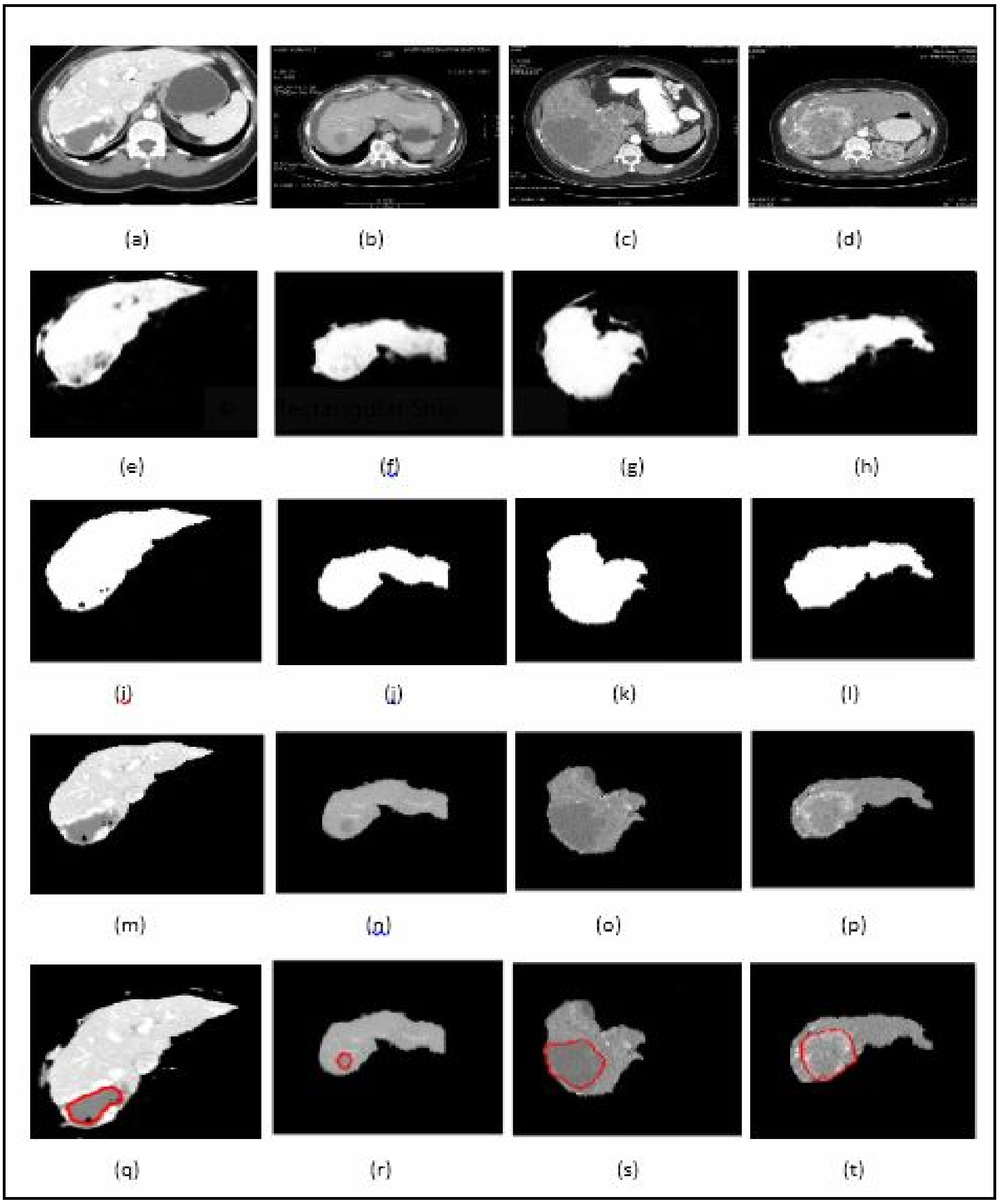

Figure 6 : (a (S6),b (S7),c (S8),d(S9)) Pre-processed images , (e,f,g,h) Neural network response ,(I,j,k,l) post processed images , (m,n,o,p) final liver segmentation output , (q,r,s,t) Liver segmentation withtumor boundary detection by lankton algorithm

4. Conclusion:

In this paper an automatic liver detection based feed forward neural network is presented. The decision based median filter is used for the noise removal in pre-processing stage. The local and texture features extracted are normalized and provides as input to neural network. During the testing stage the back propagation neural network classifies the pixels in to liver and non-liver regions. The post processing operation modifies the neural network response and the segmented liver is obtained from the abdomen CT image. The tumor boundary detection was done by localized region based active contour model. The efficiency of the neural network based liver detection is determined qualitatively by the expert radiologist and quantitatively by the similarity and success & error rate metrics. The future work will be the classification of various liver anomalies using neural network based on association rules for diagnostic purpose.

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