Enhanced Liver Tumor Diagnosis Using Data Mining and Computed Tomography (CT)

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ABSTRACT

The main objective of this study is to provide a Computer-Aided Diagnosis (CAD) system for the diagnosis process of benign and malignant liver tumors from computed tomography (CT). Also it aimed to evaluate the potential role of Fuzzy Clustering Means (FCM) and neural network in the differential diagnosis processes of liver tumors in CT images. In this study, liver tumors are classified as hepatocellular carcinoma (cancer) and hemangioma (benign). By using FCM each suspicious tumor region is automatically extracted from liver images. Consequently, textural features are obtained. These features are used to train the Neural Network (NN) and classify the tumors. The system distinguishes tumors with high accuracy and is therefore clinically useful.

KEYWORDS

Liver Tumor, CAD, Neural Network, Classification.

1. INTRODUCTION

Liver cancer has been known as one of the most dangerous diseases that causes death especially in developed countries. It has become a major health issue in the world and its occurrence has increased in the recent years. Computer Aided Diagnosis (CAD) systems based on image processing and medical imaging techniques play an important role to diagnose and cure liver cancer and hence reduce death rate. The most common medical imaging studies for early detection and diagnosis of liver tumors include Ultrasonography (US), Computed Tomography (CT), Magnetic Resonance (MR) Imaging and Angiography [1]. Computed Tomography (CT) is highly accurate for diagnosing liver tumors. Survey examinations are best undertaken with a contrast-enhanced CT study since CT has high sensibility (93%) and specificity (100%) for detecting hepatic metastases [2]. While US and Medical Resonance Imaging (MRI) also have similar accuracy, CT is preferred because it out-performs US and MRI for evaluating the extra-hepatic abdomen [3]. This paper is structured as follows: section 2 describes the review of related work. Section 3.1 describes the automatic segmentation of liver and tumor from CT image. Section 3.2 describes features extraction. Section 3.3 describes the classification process. Section 3.4 describes the performance evaluation. Experimental results and conclusion presented in sections 4 and 5.

2. RELATED WORK

Chung-Ming Wu, et al. [4] proposed a texture feature called Multiresolution Fractal (MF) feature to distinguish normal, hepatoma and cirrhosis liver using ultrasonic liver images with an accuracy of 90%. Yasser M. Kadah, et al. [5] extracted first order gray level parameters like mean and first percentile and second order gray level parameters like Contrast, Angular Second Moment, Entropy and Correlation, and trained the Functional Link Neural Network for automatic diagnosis of diffused liver diseases like fatty and cirrhosis using ultrasonic images and showed that very good diagnostic rates can be obtained using unconventional classifiers trained on actual patient data. Aleksandra Mojsilovic, et al. [6] investigated the application and advantages of the non separable wavelet transform features for diffused liver tissue characterization using B-Scan liver

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images and compared the approach with other texture measures like SGLDM (Spatial Gray Level Dependence Matrices), Fractal texture measures and Fourier measures. The classification accuracy was 87% for the SGLDM, 82% for Fourier measures and 69% for Fractal texture measures and 90% for wavelet approach. E-Liang Chen, et al. [7] used Modified Probabilistic Neural Network (MPNN) on CT abdominal images in conjunction with feature descriptors generated by fractal feature information and the gray level co occurrence matrix and classified liver tumors into hepatoma and hemangioma with an accuracy of 83%. Pavlopoulos, et al. [8] proposed a CAD system based on texture features estimated from Gray Level Difference Statistics (GLDS), SGLDM, Fractal Dimension (FD) and a novel fuzzy neural network classifier to classify a liver ultrasound images into normal, fatty and cirrhosis with accuracy in the order of 82.7%. Jae-Sung Hong, et al. [9] proposed a CAD system based on Fuzzy C Means Clustering for liver tumor extraction with an accuracy of 91% using features like area, circularity and minimum distance from liver boundary to tumor and Bayes classifier for classifying normal and abnormal slice. The CAD system proposed by Gletsos Miltiades, et al. [10] consists of two basic modules: the feature extraction and the classifier modules. In their work, region of interest (liver tumor) were identified manually from the CT liver images and then fed to the feature extraction module. The total performance of the system was 97% for validation set and 100% for testing set. Haralick transform and Hopfield Neural Network were used to segment 90% of the liver pixels correctly from the CT abdominal image by John. E. Koss, et al. [11]. However, texture based segmentation results in coarse and blockwise contour leading to poor boundary accuracy. Chien-Cheng Lee, et al. [12] identified liver region by using the fuzzy descriptors and fuzzy rules constructed using the features like location, distance, intensity, area, compactness and elongated-ness from CT abdominal images. Wen-Li Lee et al. [13] proposed a feature selection algorithm based on fractal geometry and M-band wavelet transform for the classification of normal, cirrhosis and hepatoma ultrasonic liver images. A hierarchical classifier which is based on the proposed feature extraction algorithm is at least 96.7% accurate in distinguishing between normal and abnormal liver images and is at least 93.6% accurate in distinguishing between cirrhosis and hepatoma liver images. Yu-Len Huang, et al. [14] used autocorrelation features and Multilayer Perception (MLP) Neural Network for predicting malignancies in the order of 80.5% from Non enhanced CT images. This reduced the need for iodinated contrast agent injection in CT examinations. Kumar et al. [15] proposed a method that obtains a liver segmentation by using adaptive threshold detection. Then he used FCM technique to extract tumor and curvelet transform to obtain textural information. The system obtained accuracy 94.3%.

3. IMPLEMENTATION SETTINGS AND METHODOLOGY

In the implementation work different images have been tested for benign and malignant tumors. Used images have same types and same sizes. All of this work was implemented in MATLAB programming language on a PC under Windows 7. In the proposed method the segmented tumor images used are of size 256×256.

Figure 1 illustrates an overview of the proposed method.

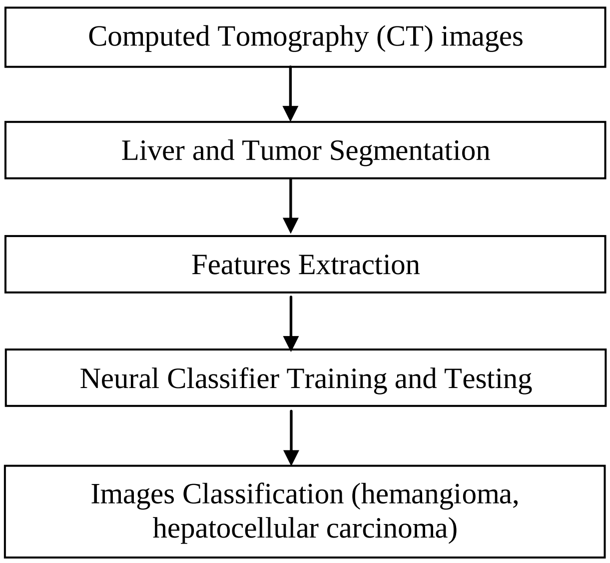

Figure 1: Overview of the Proposed Method

3.1 Liver and Tumor Extraction

Automatic liver segmentation from CT images is very difficult task, because of variations in shape, presence of neighboring structures with similar intensity, the variability of structures in the abdomen, the presence of tumors on boundaries and other abnormalities, the contrast material in

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the liver and variations in scanning protocols. Figure 2 shows the abdominal CT image.

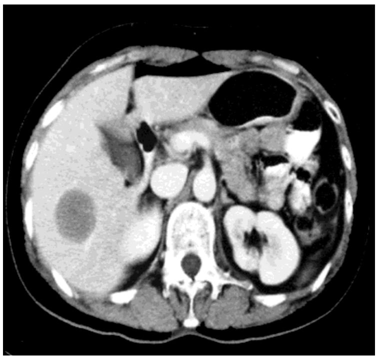

Figure 2. The abdominal CT image

The various methods used for liver segmentation are, Intensity based threshold and Multimodal thresholds [16]-[17], Statistical based model discrimination of the liver [18]-[19], the Level-set family [20]-[21], Active contour [22], Snake model [23]-[24].

Kumar et al. [25] applied median filter to reduce the granular noise present in CT image. The right bottom region of image is discarded as this region normally does not contain the liver. A histogram of the image is analyzed and the highest pitch represents the middle intensity of liver region. Figure 3 shows liver intensity.

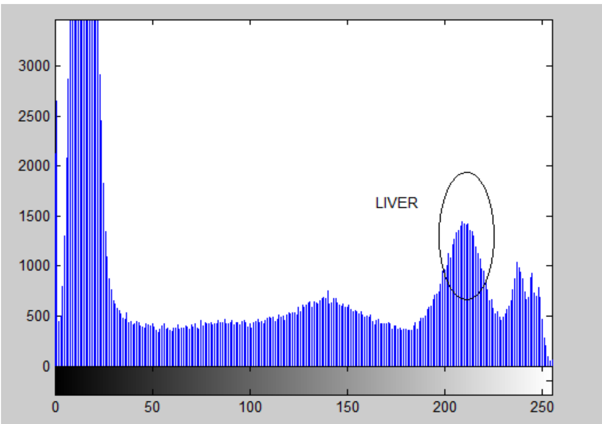

Figure 3. Plot showing liver intensity

By adaptive threshold and morphological operations liver is extracted as shown in figure 4.

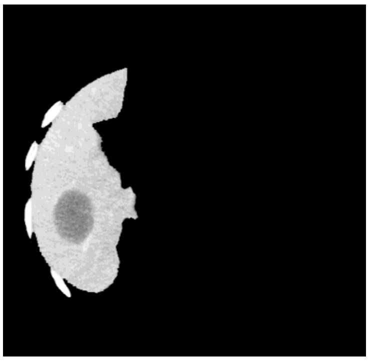

Figure 4. Segmented Liver

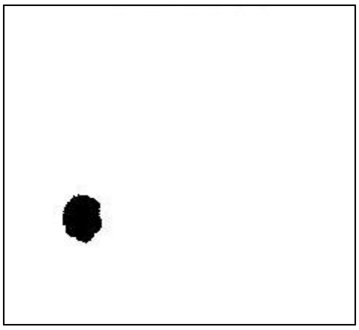

Figure 5. Segmented Tumor

Liver tumor is segmented using Fuzzy Clustering Means (FCM) as shown in figure 5 [26]. It is based on the minimization of the objective function. Partitioning by fuzzy is carried out through an iterative optimization of the membership function based on the similarity between the data and the center of a cluster. Fuzzy Clustering Means (FCM) assigns different degrees of membership to each point. The membership of a point is thus shared among various clusters. This creates the concept of a fuzzy boundaries which differs from the traditional concept of well-defined boundaries. Thus, Fuzzy Clustering Means (FCM) varies the threshold between clusters through an iterative process. As a result, the threshold is determined appropriately for every slice and the tumor region can be successfully extracted. $J_m(U,v)$ is the object function and u_{iK} is the membership function, are defined using the equations (1) , (2)

$$J_m(U,v) = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^m (d_{ik})^2 \tag{1}$$

Where,

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} (\frac{d_{ik}}{d_{jk}})^{2/(m-1)}} \tag{2}$$

d^2_{ik} is the distance between the k_{th} data (pixel value) and the center of the i_{th} cluster and v_i denotes the center value of the i_{th} cluster, which are defined by equations (3) and (4) as follows:

$$d^2_{ik} = \|X_k - V_i\| \tag{3}$$

$$v_i = \frac{\sum_{k=1}^{n} (u_{ik})^m x_k}{\sum_{k=1}^{n} (u_{ik})^m} \tag{4}$$

where x_k is the intensity of the k_{th} pixel, n is the number of data (pixels), c is the number of clusters, and m is the exponent weight. The pixels in the background (low intensity) are included in the first cluster. The second cluster includes pixels in the tumor region (medium intensity) and the pixels in the liver region other than tumor (high intensity) are included in the third cluster. The tumor region is output for further analysis [25].

3.2 Feature Extraction

Feature extraction is very important stage in pattern classification. There are several types of features extracted from the images. To build a system for the diagnosis process of benign and malignant liver tumors, we must get all available information existing in mammograms. But not all features can differentiate between benign and malignant tumors, so we used features that can do. In the proposed method a set of 10 features were calculated.

1- **Standard deviation:** It measures how values spread out in a dataset with respect to the mean.

$$s = \sqrt{\frac{\sum (x - \bar{x})^2}{n-1}} \tag{5}$$

2- **Variance:** It measures the dispersion of a set of data points around their mean value.

$$Var = s^2 \tag{6}$$

3- **Mean:** It represents the average gray level in the window.

$$\bar{x} = \frac{\sum x}{n} \tag{7}$$

4- **Skewness:** It is a measurement of the asymmetry of the data around the sample mean. If skewness is negative, the data are spread out more to the left of the mean than to the right. If skewness is positive, the data are spread out more to the right.

$$y = \frac{E(x-\mu)^3}{\sigma^3} \tag{8}$$

5- **Kurtosis:** It is a measurement of how outlier-prone a distribution is.

$$K = \frac{E(x-\mu)^4}{\sigma^4} \tag{9}$$

6- **Entropy:** A statistical measure of randomness that can be used to characterize the texture of the image.

$$S_E = -\sum_{b=a}^{L-1} P(i,j)\log_2\{P(i,j)\} \tag{10}$$

7- **Contrast:** It measures the local variations in the gray-level co-occurrence matrix.

$$CON = \sum_{i,j \in G} (i-j)^2 . co(i,j) \tag{11}$$

8- **Energy:** It provides the sum of squared elements in the gray-level co-occurrence matrix (GLCM), also known as uniformity or the angular second moment.

$$ASM = \sum_{i,j \in G} [co(i,j)]^2 \tag{12}$$

9- **Homogeneity:** It measures the closeness of distribution of elements in the gray-level co-occurrence matrix (GLCM) to the GLCM diagonal.

$$HOM = \sum_{i,j} \frac{P(i,j)}{1+|i-j|} \tag{13}$$

10- **Correlation:** It measures the joint probability occurrence of the specified pixel pairs.

$$COR = \sum_{i,j=0}^{G-1} P(i,j)(i-\mu_i)(j-\mu_j)/\sigma_i\sigma_j \tag{14}$$

Feature selection is an important part of any machine learning task. For the purpose of pattern classification, it is desirable to use an optimal number of features. The success of a classification scheme mainly depends on the features selected

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and the information they provide for their role in the model. Since a large number of features increases the computational needs, it becomes more challenging to define accurate decision boundaries in a large dimensional space. Table 1 shows a shortcut of some selected features values for benign and cancer images.

Table 1. Some Features Values for Benign and Cancer Images

Image Id	Features										
	Image class	*Standard deviation*	*Variance*	*Mean*	*Skewness*	*Kurtosis*	*Entropy*	*Contrast*	*Energy*	*Homogeneity*	*correlation*
Image1	Benign	0. 097	0.0199	0.1	- 20.2503	630.5	0.5	1.05e+002	1.3e-005	0.038	2.3364e-005
Image2	Benign	0.1	0.0123	0.9987	- 15.3746	502.3	0.1	1.06e+003	1.3e-005	0.033	3.364e-005
Image3	Benign	0.0340	0.0012	0.9989	- 28.3506	603.4	0.2	1.09e+003	1.4e-005	0.042	2.734e-005
Image4	Cancer	0.105	0.050	0.899	- 7.4706	89.5	0.1	1.08e+005	1.5e-005	0.063	4.874e-004
Image5	Cancer	0.1326	0.0936	0.9909	- 1.2546	105.55	0.2	1.09e+004	1.5e-005	0.045	5.76e-004
Image6	Cancer	0.1156	0.0783	0.9903	- 4.3256	99.3	0.1	1.09e+004	1.5e-005	0.076	4.7514e-004

In neural network and other data mining approaches texture features values obtained need to be represented in a normalized scale. Features values are scaled (normalized) in range between 0 and 1. Feature normalization is performed using the following expression.

$$Nf(x) = \frac{f(x) - \min(f(x))}{\max(f(x)) - \min(f(x))} \qquad (15)$$

Where f(x) represents the feature and min(f(x)) and max(f(x)) represents the minimum and maximum values corresponding to the feature f(x).

3.3 Classification

Classification is the process of learning a model that maps each attribute set to one of the predefined class labels. A classification technique (or classifier) is a systematic approach to building classification models from an input data set. In this study, neural network is the classification technique. Classification techniques are most suited for predicting or describing data sets with binary or nominal categories. Neural network employs a learning algorithm to identify a model that best fits the relationship between the attribute set and class label of input data. The model generated should both fit the input data well and correctly predict the class labels of records it has never seen before. Figure 6 shows the general approach for solving classification problems.

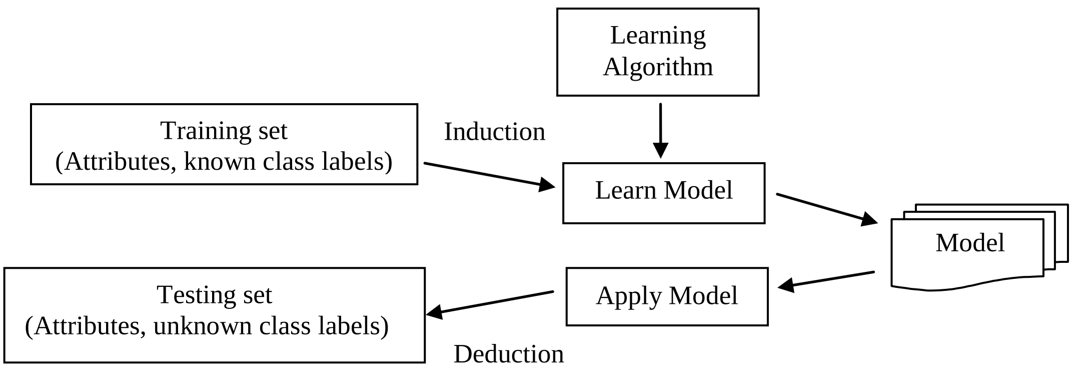

Figure 6. General approach for building a classification model

Tumor classification is carried out by using a neural network classifier. Neural networks have proven themselves as the best tool for tumor classification [27]. Neural classification consists of two processes: training and testing. A training set consisting of records whose class labels are known must be provided. The training set is used to build a classification model, which is subsequently applied to test set. Testing set consists of records with unknown class labels. The accuracy of the classification depends on the efficiency of the training process. A pattern recognition network is a feed forward network determined by activation function such as sigmoid in hidden and output layers. A neural network is a set of connected input, hidden and output units in which each connection has a weight associated with it [28]. Figure 7 shows neural network with one hidden layer and one output layer. In this study, the input layer has 10 nodes and the hidden layer has 10 nodes and the output layer has one node. The neural network trained by adjusting the weights so as to be able to predict the correct class. The output layer produce either 1 for normal or 0 for cancer.

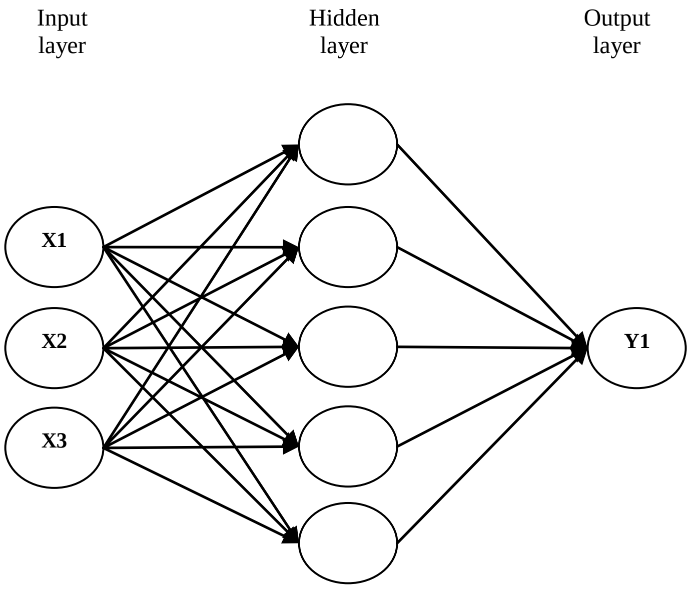

Figure 7. A sample neural network with one hidden layer

3.4 Performance Evaluation

To evaluate the performance of the classifier, sensitivity, specificity and accuracy are calculated. Sensitivity is the ratio of tumors which were marked and classified as tumor. Sensitivity=True Positive/True Positive+ False Negative. Specificity is the ratio of tumors which were not marked and also not classified as tumor. Specificity= True Negative/ True Negative+ False Positive. Accuracy measures the quality of binary classification. Receive Operating Characteristic (ROC) is plotted, confusion matrix defined as in table 2.

Table2. Confusion Matrix

Actual	Predicted	
	Positive	***Negative***
Positive	True Positives (TP)	False Positives (FP)
Negative	False Negatives (FN)	True Negatives (TN)

4. EXPERIMENTAL RESULTES

In this study, liver tumors are classified as benign and malignant. Input dataset of 100 images are divided into two groups of training and testing sets with 65 for training and 35 for testing. A set of (40 malignant, 25 benign) used for training the network, and another set of (20 malignant, 15 benign) used for testing the classifier. The confusion matrix and Receive Operating Characteristic (ROC) curve for classification are shown in figure 8 and figure 9.

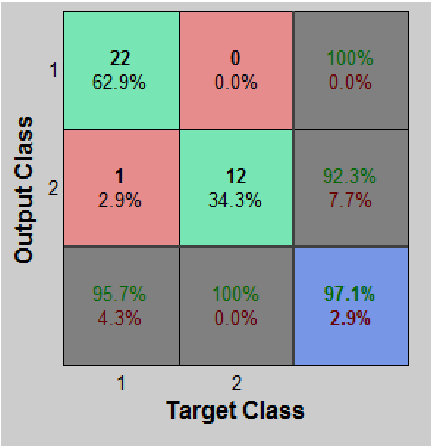

Figure 8. Confusion Matrix for testing result

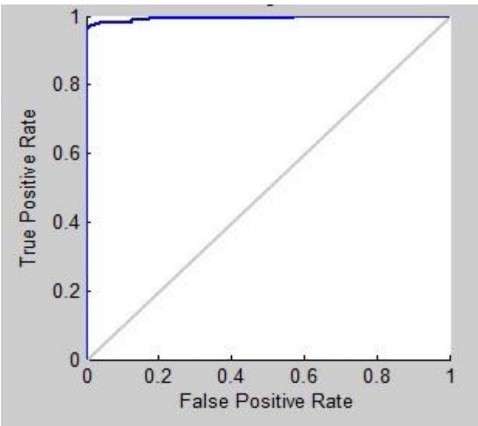

Figure 9. ROC curve for testing result

Table 3 show the computed sensitivity, specificity and accuracy for the proposed method. The obtained classification accuracy ranging between (95%) and (97.1%). At accuracy (97.1%), sensitivity and specificity are 95.7% and 100%. The overall accuracy for benign is 92.3% and for cancer is 100%.

Table 3. Performance Measures

Tested Cases	**Measures**		
	specificity	***sensitivity***	***accuracy***
35 case	100%	95.7%	97.1%

5. CONCLUSION

In this study, we propose CAD system for the diagnosis process of benign and malignant liver tumors from computed tomography through using Fuzzy Clustering Means (FCM) and Artificial Neural Network (ANN). Results show that the maximum accuracy rate for tumor classification is (97.1%). The performance can be increased more by increasing the number of samples. For future work, features combined with statistical moment features to improve the results in classification of mammogram images. The proposed system can be extended for medical diseases diagnosis.

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