

# Computer Aided Detection and Classifications of Liver Cancer Using SVM

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**Abstract -** Liver cancer is one of the common diseases that cause the death. Early detection is important to diagnose and reduce the incidence of death. Improvements in medical imaging and image processing techniques have significantly enhanced interpretation of medical images. Computer Aided Diagnosis (CAD) systems plays a major role in early detection of liver disease and in reducing liver cancer death rate. This paper presents an automated CAD system consists of three stages; firstly, automatic liver segmentation and lesion's detection. Secondly, extracting features. The liver lesions are classified as malignant and benign based on feature difference approach. Several types of intensity, texture features are extracted from both; the lesion area and its surrounding normal liver tissue. The difference between the features of both areas is then used as the new lesion descriptors. Machine learning classifiers are then trained on the new descriptors to automatically classify liver lesions into benign or malignant. Moreover, the proposed approach can overcome the problems of varying ranges of intensity and textures between patients, demographics, and imaging devices and setting.

**Keywords:** Computer aided diagnosis, support vector machine.

## I. INTRODUCTION

Liver is an important organ that performs vital functions such as detoxification of hormones, drugs, filter the blood from waste products, production of proteins required for blood clotting. However, diseases can occur without warning and early detection will help to reduce the cancer death becomes critical to successful treatment. Statistics about Global Cancer [1] has reported worldwide that the liver cancer was the fourth

major diagnosed and third leading event of death by cancer for the men. While in women, it is the seventh most frequently diagnosed and the sixth most common cause cancer death. Moreover, incidence statistic's rate of liver cancer was increasing across many parts of the world where most patients who are diagnosed with liver cancer die within six months of diagnosis. There are various imaging modalities such as Computed tomography (CT) scan, Ultrasound, X-Ray, and Magnetic Resonance Imaging (MRI) used to diagnose liver lesions. The CT scan is often preferred for diagnosing liver diseases, especially as being considered of high accurate imaging and cheaper than MRI [2], [3]. However, liver segmentation and liver lesion detection can be a very challenging task and it depends on the experience of the radiologist and that's referring to small noticeable changes between healthy liver tissue and lesion [4]. Generally, along with the improvements in image processing and artificial intelligence designing and developing systems for computer-aided diagnosis (CAD) to characterize liver lesions have received considerable attention over the past years. These systems can provide diagnostic assistance to clinicians for the improvement of diagnosis and increasing the accuracy [5]. This contributes towards avoiding the risk of liver biopsy and surgery. A general automatic/semi-automatic CAD system is supposed to provide complete assistance to doctors in diagnosis of liver cancer.

## II. EXISTING SYSTEM

Hidden Markov Model (HMM).A random sequence has the Markov property if its distribution is determined solely by its current state of the random process belong to be known as Markov random process of the system [6]. Observable state sequences that are depending on Markov chain model. All Hidden Markov Model (HMM) has non-observable states. Statistical Markov

model is one of the hidden Markov model of all models in which the system being modeled is assumed to be a Markov process with unobserved (hidden) states. An HMM can be considered as the simplest dynamic Bayesian network [7]-[8]. HMMs are composed of states, which are traversed according to transition probabilities about the sequence of the data which are being viewed from a series of all observations emitted from initial states in which an emission distribution in and over of observations which associates with each other state. HMM has three stochastic matrices separated as initial transition of observation in matrices. A square matrix and transition of matrix with A is one of the system in which it has all other probabilities in transitioning from each state to any other [9]. The transition of state  $i$  to state  $j$  have probability denoted by  $a_{ij}$ .

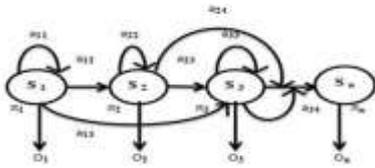


Figure-1: Structure of Hidden Markov model

Most selected Training algorithm used is the Baum Welch estimation Formulas is of finite set of each state, each of Hidden Mark Models which is associated with all of probability in distributions. Training of HMM with regarding the features according to the algorithm will reports out more effectively of all the system [10].

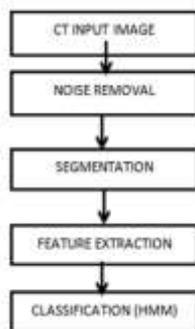


Figure-2: Block Diagram of Automatic Liver Cancer Detection

CT scans in this area are used to verify the presence or absence of tumors, infection, abnormal anatomy, or

changes of the body from trauma. The Original chest CT image is shown in figure 2.

### III. PROPOSED SYSTEM

The classification of CT in liver lesion into one of the two major classes which are Benign or Malignant that are presented in Fig. 1 is the main goal of our CAD system. First of all lesion is detected automatically and all liver is then segmented secondly. Regions of Interest (ROIs) that reflect lesion on CT images and surrounding area from normal liver tissue are extracted. Three different texture feature sets are obtained using Harr Wavelet, Tamura (Coarseness, Contrast, and Directionality) and Gabor Energy, and seven intensity features are calculated through Histogram, Mean, Variance, Skewness, Kurtosis, Energy, and Smoothness. The difference in features values from lesion of normal liver tissues are combined and then fed up into a machine learning classifier as final process. The proposed CAD system consists of three main stages that are carried out all of succession: (I) liver and lesion segmentation in each proposed system defines the lesion as first of ROI in normal liver tissues surrounding the lesion of the second one ROI (II) featuring extraction stage to extract intensity and texture all features from lesion to the surrounding areas to find one difference between them, and lesion of classification as to classify lesion into as a Benign and Malignant tumor.

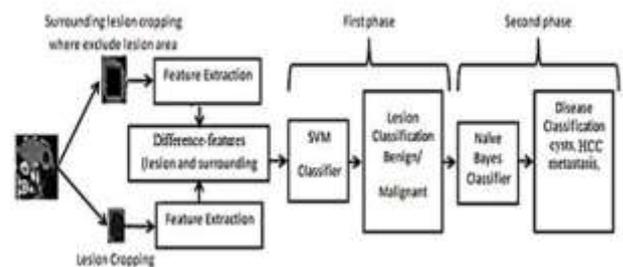


Figure-3: CAD system architecture

#### a) Liver and Lesion Segmentation

The system uses mainly a two-step process in which segmenting the liver by generating a binary liver the mask is the first step. The CT grayscale image is split into three classes using a memory efficient implementation of the fuzzy c-means (FCM) clustering algorithm.

**b) Feature Extraction**

When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (much data, but not much information) then the input data will be transformed into a reduced representation set of features (also named features vector).



Figure-4: Feature Extraction

**c) Local binary pattern features**

Local Binary Pattern (LBP) is a simple and efficient texture based operator. The LBP operator is simple for computation and consequently it becomes possible to evaluate the breast cell images in real-time applications. The LBP operator functions by labeling the pixels in the given image by means of thresholding the neighborhood of each pixel and then it stores the result as a binary number.

**d) LBP over Spatial Domain**

The LBP operator generates unique label for all the pixels in the image by thresholding the 3x3 surrounding pixels including the center value and finally stores the result as a binary number. A sub-image is obtained by placing a 3x3 mask window over the original image. In the resulting 3x3 sub image, the value of the center pixel is compared with its neighboring pixels. If the neighboring pixel has a value greater than the center pixel, then the neighboring pixel value is replaced by 1, or else the neighboring pixel value is replaced by 0.

7	1	12	1	0	1
2	5	5	0		1
5	3	0	1	0	0

**LBP = 1+4+8+64 = 77**

Pixel and its Neighbors	After thresholding	LBP Value
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Figure-5: LBP feature extraction procedure

Finally, an eight-digit binary number is formed after all the surrounding pixels are replaced.

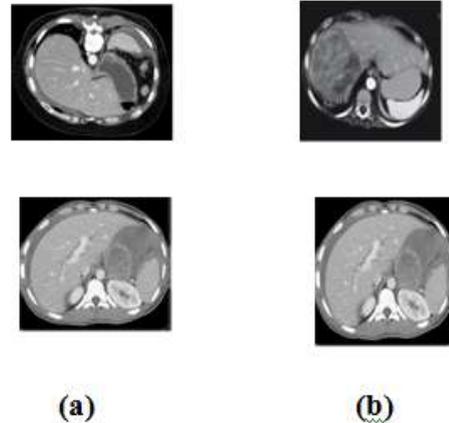


Figure-6: (a) Benign liver test image, (b) Malignant liver test image

The liver tumor diagnosis is an important criterion in medical field. We have to detect and segment the tumor area from the liver in CT image in the proposed work. The segmented liver tumor can be diagnosed using Support vector machine, which then classifies the liver tumor as benign or malignant. Then, the performance analysis is carried out in terms of sensitivity, specificity, positive predictive value, negative predictive value and Accuracy. Fig 6 shows the dataset used in this work. The dataset includes benign and malignant tumor images of the liver.

**e) SVM Classifier**

SVMs are an arrangement of related and administered learning strategies that break down information and perceive designs, utilized for order and relapse investigation. The standard SVM takes an arrangement of info information, and predicts, for each given information, which of two conceivable classes the information is an individual from, which makes the SVM a non-probabilistic parallel straight classifier. Since a SVM is a classifier, at that point given an arrangement of preparing illustrations, each set apart as having a place with one of two classifications, a SVM preparing calculation fabricates a model that predicts whether another case falls into one class or the other. SVM isolates an arrangement of preparing pictures into two distinct classes, over a dimensional element space.

#### IV. CONCLUSION

Another technique and approval think about for the Computer Aided Detection and order of Liver Cancer utilizing SVM. The tumor division technique proposed in this paper incorporates a novel strategy for tumor order which helps the medicinal specialists for encourage analysis. The upside of our technique is that it yields exact outcomes for various sorts of liver tumor easily and without manual interation.

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