Uplifted Tissue Characterization and Classification of Fatty Liver Disease from Ultrasound Images

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ABSTRACT
A fatty liver is the result of the extra fat in liver cells and it causes deadly diseases such as liver cancer, fibrosis, cirrhosis, tumor and so on. For detecting fatty liver disease, we have developed a new system called ultrasound based Computer-Aided Diagnosis system. We have used Thershold with Median Filter to remove speckle noise from images. We use image texture based features like Entropy and Local Binary Pattern (LBP). To classify the liver image, we have used a built-in classifier: the Support Vector Machine (SVM), and a Polynomial Kernel function. It has been chosen for its accuracy. We have also used K-means Cluster rule to provides best product, once data set are well separated from one another. It can achieve better classification between the fatty liver tissues and normal tissues. Therefore, our proposed system is very efficient into hospital workflows and has been used in a clinical setting to obtain more reproducible results with high accuracy, reliability, speed and objectiveness of the diagnosis of fatty liver disease.

Keywords:-*Fatty liver disease, ultrasound image, computer-aided diagnosis, support vector machine, polynomial kernel function, entropy, local binary pattern, median filter, k-means clustering, classification, characterization.*

INTRODUCTION

Fatty Liver Disease (FLD) is a major issue at medical science of various reasons. Obesity, genetic factors, use of drugs and chemicals are common causes for this disease. 15% people of the present world are affected by this disease [1]. A fatty liver is the result of the extra fat in liver cells. A person has a fatty liver when fat makes up at least 5% of the liver. Research revealed that the prevalence of FLD depends on sex, ethnicity and age [2]. Even though many research have been published in this area, but, still needs a of studies that use images from multi-center large scale clinical trials to determine an optimal feature set-classifier combination that presents excellent accuracy, sensitivity, and specificity. Most Computer-Aided Diagnosis system (CAD) research focus on classifying a normal liver from FLD affected or cirrhotic liver.

There are many diagnosis techniques for detecting Fatty Liver Disease (FLD). Nowadays, doctor are refered non-invasive technique for diagnosis FLD. Among all noninvasive techniques, Ultrasound (US) is the most common and widely used imaging modality for FLD diagnosis, because it is inexpensive, emits no harmful radiation, is widely available and has high sensitivity [3]. Ultrasound is the most effective process to diagnosis FLD, comparing with other processes such as Blood Test, Biopsy, Computed

Tomography (CT) scan and Magnetic Resonance Imaging (MRI). We want to develop a system which is Ultrasound based Computer-Aided Diagnosis system (US CAD). We have expected that our proposed system will be better effective for fatty liver image classification than other systems. Moreover, compared to the traditional histological evaluation method, CAD based systems have the following advantages: simple to use, less bias, no user dependency, objective reproducible results, increased speed, and lower operational cost.

In this paper, firstly, we have reviewed the advantages and limitations of current modalities that are used for FLD detection (Section-2: Literature Review). Subsequently, we have discussed the structure of an US-based CAD system and briefly describe the features that are extracted from the US images and the commonly used classification algorithms (Section-3: Methodology). Then,We have reviewed the methodology and evaluation results of several CAD systems proposed in the literature (Section-4: Analysis, Design and Development). After careful analysis of the literature, we have found that the US-based CAD techniques for FLD can improve accuracy, speed and objectiveness of the diagnosis, and thereby, reduce operator dependability (Section-5: Result and Discussion). Finally, we have conclude the paper in (Section-6: Conclusion).
Contributions of this research are:

- Reviewing the advantage and limitations of current systems that are used for Fatty Liver Disease (FLD) detection without ultrasound based Computer-Aided Diagnosis (CAD) system.
- Describing the ultrasound based Computer-Aided Diagnosis (CAD) system.
- Describing the features that are extracted from the ultrasound images and the used algorithm briefly.
- Using the features as input to train automated decision making systems.
- Analysis of the literature so that we find the ultrasound based Computer-Aided Diagnosis (CAD) system that can improve accuracy, speed and objectiveness of the diagnosis.

LITERATURE REVIEW

İn human body, the tissue consists of group of cells with a similar structure working together for a specific function. There are four types of tissues: muscle tissue, connective tissue, epithelial tissue and nervous tissue.

The liver is the heaviest and the largest glandular organ in the human body and it is absolutely crucial to life. One of the main functions of liver is detoxification of the body by filtering potential harmful biochemical products from the blood. Health care providers divide this type of fatty liver disease into 2 subtypes. If a person just have fat deposition in hepatocytes, but no signs of damage / inflammation in his/her liver, the disease is called Nonalcoholic Fatty Liver Disease (NAFLD). If a person have fat deposits in his/her liver plus signs of inflammation and liver cell damage, the disease is called Nonalcoholic Steatohepatitis [4]. Sometimes it is called a silent liver disease. Therefore, it can be happened without causing any symptoms. Normal liver is usually homogeneous and characterized by a dark and neat granular pattern, whereas an FLD affected liver appears brighter and smoother [1].

Nowadays, many current methods is used for detecting fatty liver disease [5]. There are two type of diagnosis techniques. One is invasive and other is non-invasive. Hence, we need to develop a method which is reliable, noninvasive and cost efficient method for assessing the liver fat content. Noninvasive techniques imaging with high accuracy and sensitivity are crucial to FLD screening. These diagnosis methods are briefly describe in the following paragraphs and according to the benefits and issues of these methods, we present a summary.

CT scan, also known as computerized axial tomography scan (CAT scan) or X-ray computed tomography (X-ray CT). CT is a noninvasive medical diagnosis tool that uses multiple X-ray images to produce tomographic models of specific areas of the human body. It also allows the user to see inside the object without cutting. CT provides correct high distinction images of the entire liver [6]. Steatosis of the liver is better visible in images from unenhanced CT than from enhanced CT. Images from unenhanced CT show the normal liver with a slightly higher attenuation when compared to spleen and blood. İn CT, major issue is harmful radiation and this restricts it from being used in repeated studies and in children [7]. Hence, there is a need to an accurate modality like MRI.

Magnetic Resonance Imaging (MRI), Nuclear Magnetic Resonance Imaging (NMRI), or Magnetic Resonance Tomography (MRT) which are employing the radiology to imaging the anatomy of the body in both for health and disease. Magnetic fields and radio waves are used in MRI scanners to form images of the body. Therefore, it is more useful in imaging soft tissues in the body, such as liver, brain, heart and muscles. Unlike US, MRI is operator independent [8]. The decrease of signal intensity to an out-of-phase from an in-phase image denotes the current of liver fat. The amount of fat is calculated by measuring the total decrease of signal intensity. MRI machines in the market do not come with that capability. MR imaging techniques are relatively costly, and hence, they are not widely available. It is not recommended for patients with implanted electronic devices or ferromagnetic metal implants [1]. Now, we need a low-cost, radiation free and readily available modality like US (Ultrasound Image).

For over half a century, ultrasound has been used to image the human body. An Austrian neurologist, Dr. Karl Theo Dussik first applied ultrasound as a medical diagnostic tool to image the brain. Ultrasound image can give us the internal structure and statistical measurement of the affected organ instead of others imaging technique like MRI, CT scan. İt is widely used [9]. US for designation, FLD is its operator responsibility. Even though the sensitivity and specificity of US in detecting FLD is acceptable, the weakness of this screening modality is in reproducibility and reliability in detecting steatosis. Due to this problem, we have developed a new system, ultrasound based Computer-aided Diagnosis system that can improve accuracy, speed and objectiveness of the diagnosis.

Medical ultrasound devices use sound waves in the range of 1–20 MHz [10].

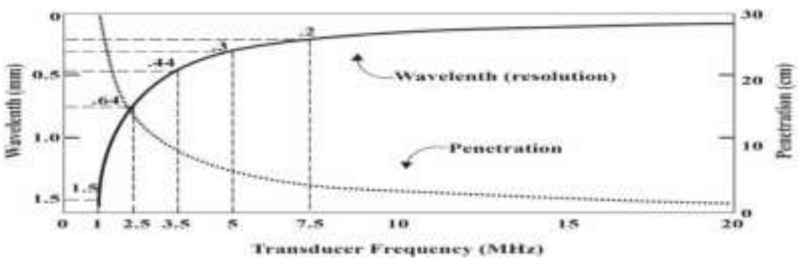


Fig.1:*-A comparison of the resolution and penetration of different ultrasound transducer frequencies*

The transducer is each a sender and receiver. In addition, it is placed within the water, or during a medium adjacent to the water, and emits an acoustic signal with a characteristic wave form. Once a part of the acoustic signal strikes an object, it is reflected back to the transducer, that receives it and sends it to the processor. The processor/display may be a cluster of electronic circuits that interprets the signals received by the transducer [11]. The resistance to the propagation of ultrasound waves through the body tissues and organs [12]. In Table-1 show the different body tissues and organs acoustic impedance.

Table 1:-*Acoustic impedances of different body tissues and organs*

Body tissue	Acoustic impedance (106 Rayls)
Bone	8.0
Muscle	1.73
Liver	1.67
Blood	1.67
Spleen	1.66
Fat	1.65
Water	1.52
Kidney	1.36
Lung	0.20
Air	0.0006

Table 2:-*Summary of clinical examination result*

Techniques	Advantages	Limitations
CT scan	-Depicts steatosis by lower liver intensity -Provides accurate high contrast images of the entire liver -Quantitative measurement	-Operator dependent -Poor sensitivity for early steatosis -Harmful radiation
MRI	-Good quantification of the fat of the liver -Possibility of spectroscopy analysis -Operator independent	-Fat quantification inaccuracies in the presence of high iron concentration -High cost of Examination and not widely available -Unsuitable for subjects with implemented electronic devices
Ultrasound	-Prescribe for initial diagnosis -Low cost, non-invasive, safe -Radiation free and readily available	-Operator dependent -Intra-operator variability -Unsuitable for subject with high BMI

METHODOLOGY

Computer Aıded Dıagnosıs (CAD) System

Computer-aided diagnosis (CAD) has become one of the major important subjects in medical imaging and diagnostic radiology. CAD is to supply a computer output as a second opinion to help radiologist's image interpretation by improving the consistency of radiological diagnosis and therefore the accuracy and also by reducing the image reading time. The block diagram of a CAD system given below:

PROPOSED METHOD

The proposed method is to address polynomial function as a kernel in the SVM model. This method is chosen for its accuracy. This method provides more accurate output and relatively it is easy to use. The block diagram of our proposed method:

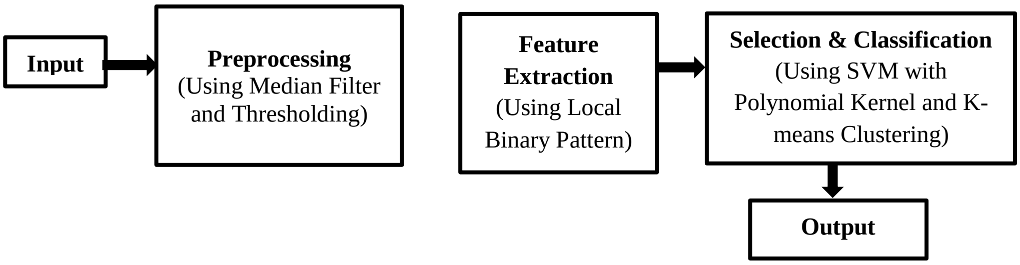


***Fig.2:**-Block diagram of proposed method*

Pre-Processing

Median Filter

The image pre-processing or data pre-processing means change the image dimension, clean the noise which is added when take the image. Median filtering used to remove noise from images. It is particularly effective at removing speckle type noise. The median filter can move through the image pixel by pixel, replacing each value with the median value of neighboring pixels.

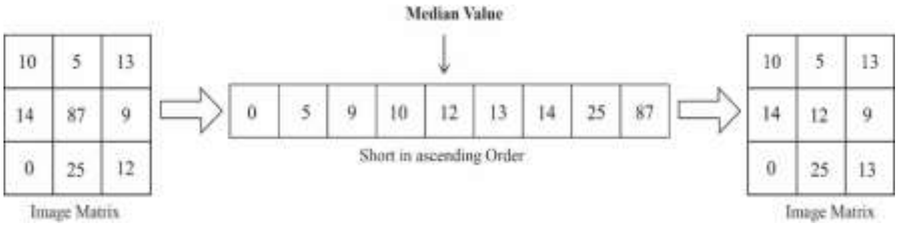


***Fig.3:**-Basic operation of median filter*

Feature Extraction and Selection

In image processing and computer vision, a feature is a piece of information which is applicable for solving the computational task related to a certain application. Features may be specific structures in the image such as edges, points or objects. We use Local Binary Pattern (LBP) to extract feature and feature selection.

Entropy

Entropy is a measure of uncertainty which is associated with the randomness of the measured entity. The entropy of a system as defined by Shannon which gives a measure of uncertainty about its actual structure [10].

Let, the image I(q, r) have D_g distinct gray values, where g = 0, 1, 2,………. ,Li-1 .

The normalized histogram for a region of interest of size (ExF) is defined as:

$$P_g = \frac{D_g}{EF}$$

Shanon Entropy is given by:

$$S_n = \sum_{g=0}^{Z-1} P_g log2P_g$$

Local Binary Pattern

The Local Binary Pattern (LBP) method has been applied in many applications [13]. By using a 3 × 3 operator a feature can be computed, only relating to a small image structure that may not necessarily be adept to capture the key texture characteristic. However, LBP using circular neighborhoods and linearly interpolating the pixel values allows the choice of any radius R, and number of pixel in the neighborhood P, to form an operator, which can model large scale structure. The Local Binary Pattern (LBP) equation is shown below:

$$\text{LBP P,R(x,y)}=\sum_{P=0}^{P-1} S \ \text{S(X)}= \begin{cases} 1, if x \geq 0 \\ 0, if X < 0 \end{cases}$$

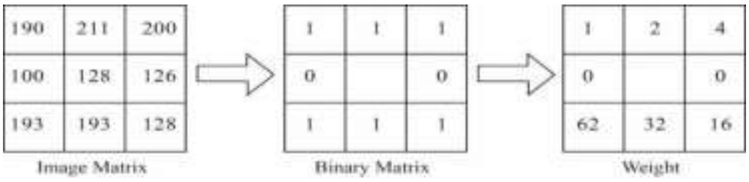


Fig.4:-*The basic of LBP operator*

The Weight, W=1+2+4+16+32+62 =119

Classıfıcatıon

To classify the liver image we use built-in classifier the support vector machine (SVM), and a kernel function. The kernel function is polynomial kernel method. used K-means Cluster rule to provides best product, once data set are well separated from one another. It can achieve better classification between the fatty liver tissues and normal tissues.

Support Vector Machıne (SVM)

In machine learning, for classification and regression analysis, support vector machines are supervised learning models with associated learning algorithms that analyze data and recognize patterns are used. A SVM model is a representation of the examples as points in space and mapped [14].

Kernel Function Using Polynomial

Many common functions are polynomial functions. Here, we describe polynomial functions and concentrate at some of their properties.

$$f(x) = a_n X^n + a_{n-1} X^{n-1} + \cdots + a_2 X^2 + a_1 X + a_0$$

Where n is a non-negative integer and an ≠ 0. The numbers a_1, a_2, a_3, a_4, a_5… an are called the coefficient of the polynomial. The number a_0 is the constant term or constant coefficient. The number and the coefficient of the highest power is the term $a_n X^n$ and it is the leading term and the leading coefficient. p is the order of the polynomial. Support vector machines is a class of machine learning algorithms. Polynomial kernels used with SVMs include:

$$K(X_1 X_2) = (X_1^T X_2 + 1)^p$$

Turning Points of Polynomial Functions

A turning point of a function is a point where the graph of the function changes from sloping downwards to sloping upwards, or vice versa. For this reason, the gradient is changes from the positive to negative or from the negative to positive. Generally, curves of degree n can have up to (n − 1) turning points [15].

K-Means Clusterıng

The K-means clustering algorithm is one of the simplest unsupervised learning algorithms in machine learning. It can solve the well-known clustering problem. To classify a given data set through a certain number of clusters fixed a priori the procedure follows a simple and easy way. Here, a squared error function, this algorithm aims at minimizing an objective function [16]. To get minimizing an objective function by calculating distance between clusters. The formula is shown in below,

Distance = $\sqrt{(x_1 - x_2)^2 - (y_1 - y_2)^2}$

ANALYSIS, DESIGN AND DEVELOPMENT

Evaluatıon Crıterıa

Signal-to-Noise Ratio

The Signal-to-Noise Ratio (SNR) is employed in imaging as a physical live of the sensitivity of associate imaging system. In Industry level measure, SNR in decibels (dB) of power and therefore apply the 10 log rule to the "pure" SNR ratio [17]. Traditionally, SNR is the ratio of the average signal value μ_{sig} to the standard deviation σ_{bg} of the background.

The MATLAB built-in function SNR $= \frac{\mu_{sig}}{\sigma_{bg}}$

Mean Squared Error

Statistically, the Mean Squared Error (MSE) of an estimator measures. It measures the average of the squares of the "errors", that is, the difference between the estimator and what is the estimated. Corresponding to the expected value of the squared error loss or quadratic loss MSE is a risk function. If $\hat{Y}$ is a vector of η predictions, and Y is the vector of observed values corresponding to the inputs to the function which generated the predictions. Here, free m × n monochrome image I and its noisy approximation K, MSE is defined as:

$$\text{MSE} = \frac{1}{mn}\sum_{i=1}^{m-1}\sum_{j=0}^{n-1}\left[I(i,j) - K(i,j)\right]^2$$

Peak Signal-to-Noise Ratio

PSNR (Peak Signal-to-Noise Ratio) may be a term of engineering that is expressed by the ratio between the utmost possible power of a sign and therefore the power of corrupting noise. The PSNR (in dB) is defined as:

$$PSNR = 10log_{10}\left(\frac{MAX_i^2}{MSE}\right) = 20log_{10}\left(\frac{MAX_i^2}{\sqrt{MSE}}\right)$$
$$= 20log_{10}$$

EVALUATİON RESULT

Table 3:-*Evaluation result of images*

	Noisy Image	Original Image
SNR	8.0738	11.3992
PSNR	26.9081	31.6764
MSE	38.5996	17.9028

Accuracy

The accuracy of a measurement system in the fields of engineering, statistics and science is the degree of closeness of measurements of a quantity to that quantity's true value. The general equation of accuracy:

Accuracy

$$= \frac{\text{number of true negatives} + \text{number of true positive}}{\text{number of true negative} + \text{false negative} + \text{number of true positives} + \text{false positive}}$$

Sensitivity

Sensitivity relates to the test's ability to correctly detect patients who do have the condition. Now, we consider the example of a medical test used to identify a disease. Mathematically, this can be expressed as:

$$\text{Sensitivity} = \frac{\text{number of true positives}}{\text{number of false negative} + \text{number of true positives}}$$

Specificity

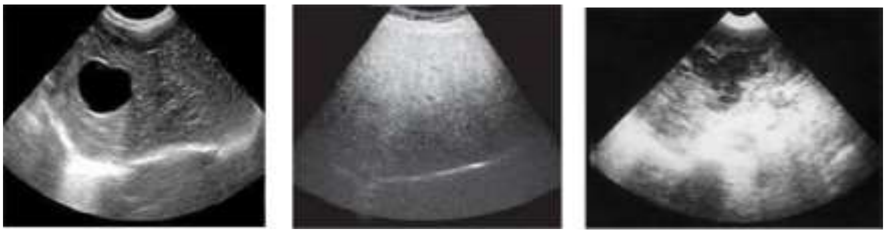
Specificity tends to the test's ability to correctly detect patients without a condition. Specificity of a test is the proportion of healthy patients, who will test negative for it known not to have the disease. Mathematically, this can also be written as:

$$\text{Specificity} = \frac{\text{number of true negatives}}{\text{number of false positives} + \text{number of true negatives}}$$

Table 4:-*Summary of studies that proposed techniques for FLD diagnosis*

	K-Means	Wavelet Algorithm	SVM with Polynomial
Accuracy	87%	91%	95%
Sensitivity	88%	78%	90%
Specificity	77%	75%	80%

Input Image



1 2 3

***Fig.5:-** Input image*

Pre-Processıng

Convert the image from RGB to Gray scale:

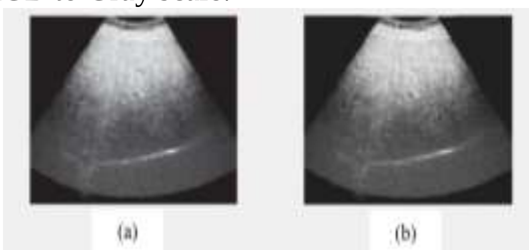


***Fig.6:-** (a) Color image and (b) gray scale image*

Noise Reduction using median filter:

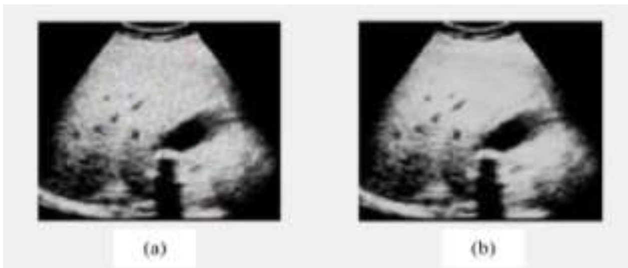


***Fig.7:-**(a) Noisy image and (b) Filtered image*

Thresholding in the image using MATLAB:

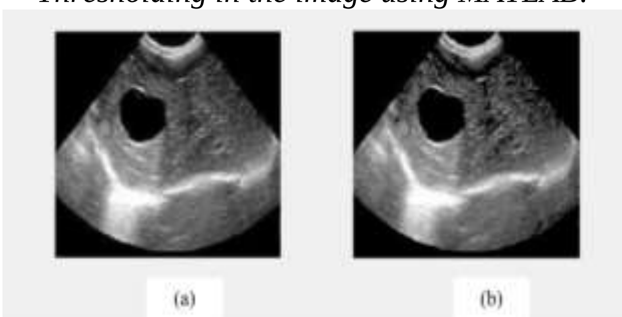


***Fig.8:-**(a) Gray scale image and (b) after thresholding image*

Evaluation Table

***Table 5:-**For image 1*

	Noisy Image	Filtered Image
SNR	8.0738	11.3992
PSNR	26.9081	31.6764
MSE	38.5996	17.9028

***Table 6:**-For image 2*

	Noisy Image	Filtered Image
SNR	7.4728	10.7922
PSNR	25.5800	30.6658
MSE	45.0356	20.8871

***Table 7:**-For image 3*

	Noisy Image	Filtered Image
SNR	7.6634	8.9122
PSNR	23.5213	27.4126
MSE	39.8825	29.9264

Feature Extractıon and Selectıon

In this section we extract the feature of ultrasound (US) liver image and select the feature for detecting fatty liver disease (FLD), by using Local Binary Pattern (LBP).

For Image 1:

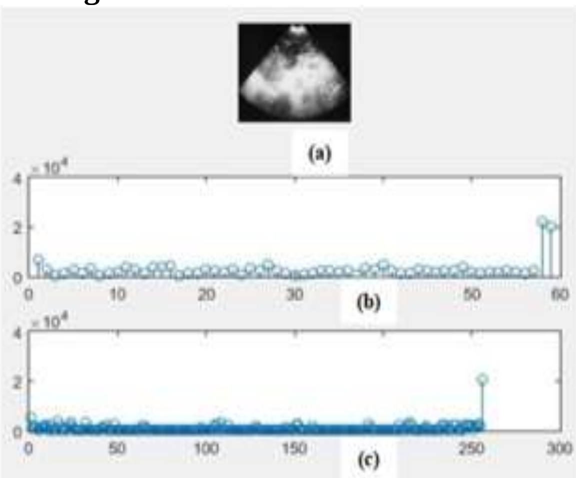


***Fig.9:**-(a) Gray scale image and (b, c) is the Histogram of the image 1*

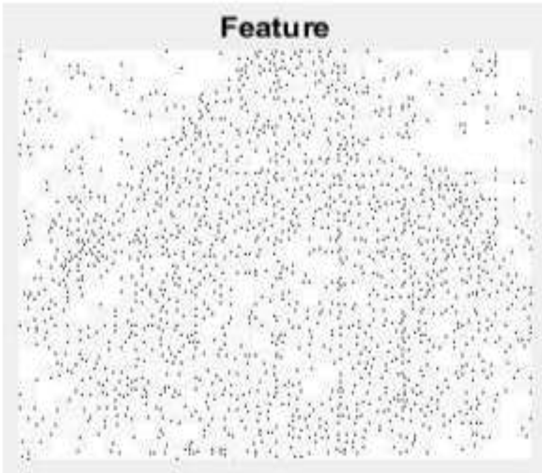


***Fig.10:**- Feature of the image 1*

For Image 2:

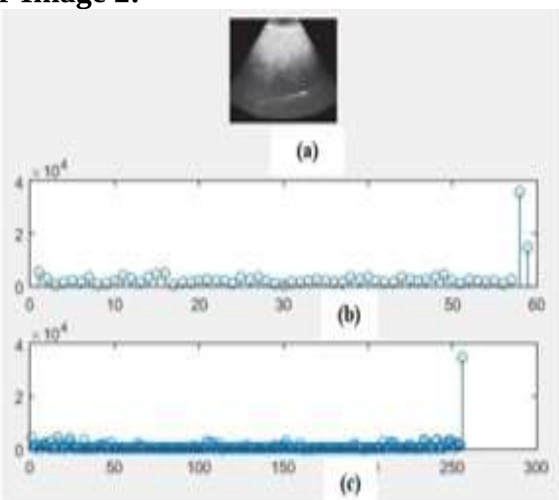


***Fig.11:**- (a) Gray scale image and (b, c) is the Histogram of the image 2*

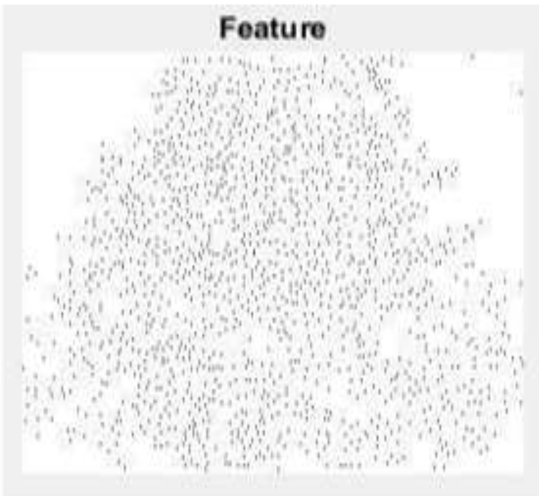


***Fig.12:**-Feature of the image 2*

For Image 3:

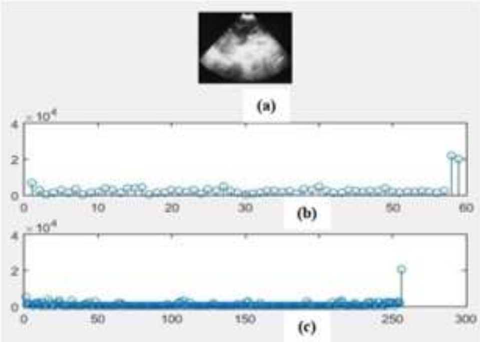


Fig.13:- *(a) Gray scale image and (b, c) is the histogram of the image 3*

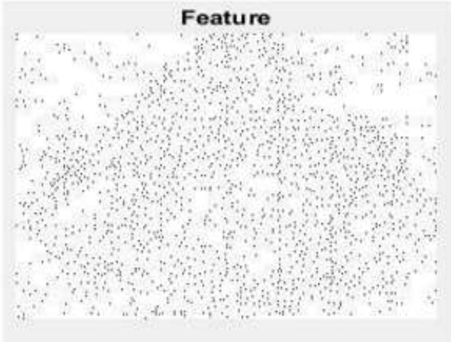


Fig.14:-*Feature of the image 3*

Classıfıcatıon (Output)

Output for image 1:

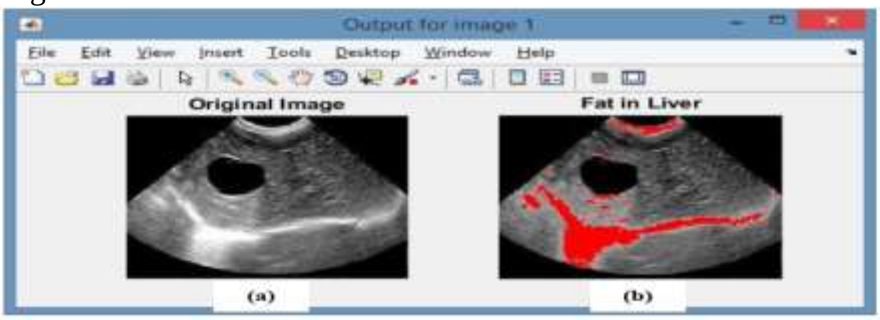


Fig.15:-*(a) Normal fatty liver (b) fatty liver tissues with red marked*

```
Command Window
  This is a fatty liver.
  Fat in liver = 13.13%
fx >>
```

Fig.16:- *Result with percentage of Fat*

Output for image 2:

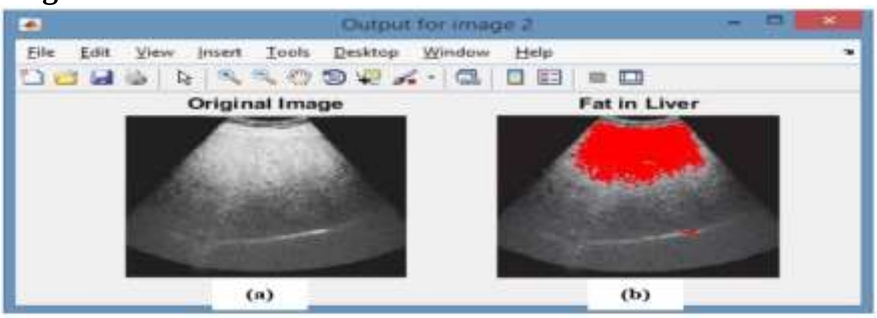


Fig.17:-*(a) Normal fatty liver (b) fatty liver tissues with red marked.*

```
Command Window
  This is a fatty liver.
  Fat in liver = 12.85%
fx >>
```

Fig.18:-*Result with percentage of fat*

Output for image 3:

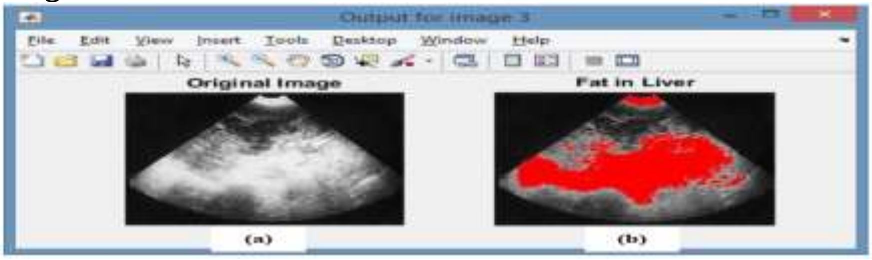


Fig.19:-*(a) Normal fatty liver (b) fatty liver tissues with red marked*

Fig.20:-*Result with percentage of Fat*

RESULT AND DISCUSSION

We present a comparison between other systems and our proposed system in Table 8. Firstly, Yeh et al. [18] developed a method to differentiate steatosis and non-steatosis liver specimens imaged exploitation high frequency US using GLC and SVM and achieve 90.5% accuracy. Secondly, Graif et al. [19] developed an automatic Far-Field Slope (FFS) algorithm used US video images/normal, fatty on various degrees of fatty infiltration and achieved Accuracy: 85% Sensitivity 100%, Specificity 60%, PPV 80%, NPV 100%. Thirdly, Ribeiro et al. [20] prescribed Radio Frequency (RF) signal generated by the US where intensity features were estimated from the despeckled image and classification was done on two image sets, using a Bayes classifier, hence achieved Accuracy 95%, Sensitivity 100%, Specificity 95%. Fourthly, K. Mala [21] was used to Orthogonal wavelet transform on CT and hence achieved Accuracy 95%, Sensitivity 96%, Specificity 94%. Fifthly, Acharya et al. [22] applied three texture, wavelet transform and higher order spectra features; decision tree classifier and observed Accuracy of 93.3%. Finally, in our propose system (Ultrasound based Computer Aided Dignosis System) using Polynomial function as a kernel in the SVM model, we achieve 95.33% accuracy.

Table 8:-*Summary of CAD studies that proposed techniques for FLD diagnosis.*

Author	Modality/classes	Features/Techniques	Performance measures
Yeh et al. [18]	US images of fresh human liver samples	GLC features/SVM Classifier	Accuracy: 90.5%
Graif et al. [19]	US video images/normal, fatty (in the same patients)	FFS algorithm based	Accuracy: 85% Sensitivity: 100% Specificity: 60%
Ribeiro et al. [20]	US envelope RF image/normal, fatty	Three intensity and texture features/Bayes classifier	Accuracy: 95% Sensitivity: 100% Specificity: 95%
K. Mala[21]	CT	Orthogonal wavelet transform	Accuracy: 95% Sensitivity: 96% Specificity: 94%
Acharya et al. [22]	US/normal, fatty	Three texture, wavelet transform and higher order spectra features; decision tree classifier	Accuracy: 93.3%
Our propose system (Ultrasound based Computer Aided Dignosis System)	US/normal, fatty	Polynomial function as a kernel in the SVM model	Accuracy: 95.33%

CONCLUSION

Fatty liver disease (FLD) is a progressively prevalent disease at present world due to various reasons. We have developed a new system called Ultrasound based Computer Aided Dignosis System for detecting FLD. Here, we have applied thresholding with median filter to reduce speckle noise from ultrasound image. Then, we have used local binary pattern for feature extraction. Finally, we have used polynomial function as a kernel in the SVM model and K-means clustering for ultrasound image classification. These methods is chosen for its accuracy. Our system provides more accurate output and relatively it is easy to use. In future, we will work in 3D ultrasound image and will detect the precondition of liver tissue before it turns to fatty liver.

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