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# Machine Learning based Early Stage Identification of Liver Tumor using Ultrasound Images

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**Abstract:** Liver cancer is one of the most malignant diseases and its diagnosis requires more computational time. It can be minimized by applying a Machine learning algorithm for the diagnosis of cancer. The existing machine learning technique uses only the color-based methods to classify images which are not efficient. So, it is proposed to use texture-based classification for diagnosis. The input image is resized and pre-processed by Gaussian filters. The features are extracted by applying Gray level co-occurrence matrix (GLCM) and Local binary pattern (LBP in the preprocessed image. The Local Binary Pattern (LBP) is an efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number. The extracted features are classified by multi-support vector machine (Multi SVM) and K-Nearest Neighbor (K-NN) algorithms. The Advantage of combining SVM with KNN is that SVM measures a large number of values whereas KNN accurately measures point values. The results obtained from the proposed techniques achieved high precision, accuracy, sensitivity and specificity than the existing method.

**Keywords:** Ultrasound imaging, Multi-Support vector machine, Kernel, GLCM, LBP

## 1. Introduction

Cancer is a dangerous disease characterized by abnormal cell growth that has the potential to invade or spread to other parts of the body. Liver cancer is the most dangerous one [1]. For the diagnosis of liver cancer, computer-aided diagnosis (CAD) provides an output as a second opinion in order to assist radiologists in the diagnosis of various diseases on medical images. It is estimated that by the year 2022 around 830,180 people would die due to liver cancer. To help hepatologists and to improve diagnostic accuracy, machine learning techniques play a vital role in the diagnosis of liver cancer [2]. In the Ultrasound scanning technique, patients aren't exposed to the ionizing radiations, making them safer than the diagnostic techniques such as X-rays and

CT scans. Ultrasound images provide high clarity images of soft tissues than the X-rays and CT scan images.

The exact cause of liver cancer is associated with damage and scarring of the liver known as cirrhosis. The existing methodology, CAD system diagnoses liver cancer using the features of excrescence tumour attained from ultrasound images. Ultrasound images are used in the diagnosis of liver tissues, due to their ability to visualize human tissue exactly without deleterious effects [3]. The input data is transformed into a set of features called feature extraction. The characterization of liver images in this existing is based on texture analysis-based techniques [4]. There exist a considerable number of texture analysis techniques but GLCM is one of the finest algorithms. Texture analysis aims in finding a unique way of representing the underlying characteristics of textures and represent the feature values in some simpler but unique form so that they can be used for accurate classification [5]. The most common are first-order statistics, and gray level co-occurrence matrix (GLCM). It is a second-order statistics method, which is based on (local) information about gray levels in pair of pixels. The matrix is defined over the image with the distribution of co-occurring values of the given offset. Harlick described 22 statistical feature measures that can be calculated from the co-occurrence matrix with the intent to describe the texture of the images. The matrix element P (i, j | x, y) is the relative frequency with which two pixels, got separated by a pixel distance (x, y), occur within a given neighborhood, one with the assigned intensity I and the other with intensity j. The matrix element P (i, j | d,) contains the second-order statistical probability values for changes between gray levels i and j at a particular displacement distance and a particular angle

A classifier system is a machine learning algorithm that learns syntactically simple rules to guide its performance improved in an arbitrary environment. A nonparallel hyper plane-based SVM+ (NHSVM+) is first proposed to improve the TL performance by transferring the per-class knowledge from the source domain to the corresponding target domain [6]. As a variant of SVM, the nonparallel hyperplane-based SVM (NHSVM) provides a way to discriminate the data with a more complex distribution, which handled the complex classification task by minimizing the within-class difference and maximizing the difference between classes during the learning process [7]. Due to its superior performance, improved NHSVM algorithms have been proposed for this classification tasks

The organization of the paper as follows: Proposed method is presented in section 2. Experimental results are discussed in section 3. Section 4 concludes the paper.

## 2. Proposed Method

Since invasive methods cause pain and discomfort, non-invasive methods are introduced. These non-invasive methods include computer-aided diagnosis and time-efficient methods using ultrasound images [8]. This method is accomplished by feeding input images from the dataset to the working platform. The standard of the image is improved by pre-processing which helps us in analyzing the image in a better way. By Pre-processing, the undesired distortions are suppressed removing noise through a Gaussian filter. The other two major processes are feature extraction and classification which are performed by two algorithms such as GLCM and LBP and classification is done by two algorithms such as Multi-SVM and K-NN [9, 10]. The proposed work flow is shown in Figure 1.

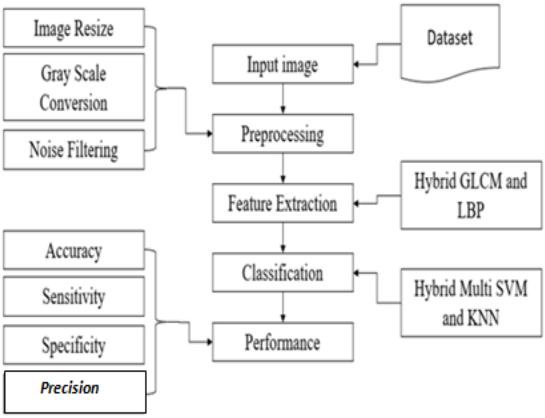



**Figure1.** Proposed Flow Diagram

### *2.1 Preprocessing*

The Main idea of pre-processing is to suppress the unwanted distortions and enhance features for further processing. The steps involved in pre-processing are image resize, noise filtering, and Grayscale conversion. Image is resized for appropriate pixel levels to be processed by the system to achieve enhanced images. The noise filtering technique is done to remove the unwanted pixels in the image by the use of a Gaussian filter. Gaussian smoothing is the result of blurring an image by a Gaussian function in image processing. The smoothening of images is essential and is required to remove the noise and for that standard filter is used in most image processing applications. Grayscale conversion is used for converting RGB images into Grayscale images. It is used for simplifying the algorithm and reducing the complexity. The luminance can also be described as intensity this can be measured on a scale from black to white. Image file formats are supported by a minimum of 8-bit grayscale, which yields 2^8 or 256 levels of luminance per pixel but in RGB images supported by 24-bit RGB which yields 2^24 or 16777216 levels of luminance per pixel so it is better to convert the image as a grayscale image. In a few formats, 16-bit grayscale is supported by a 2^16 level of luminance.

### *2.2 Feature Extraction*

The features are extracted from the pre-processed images by combining the Gray level co-occurrence matrix (GLCM) and the Local binary pattern (LBP). Several texture features may be extracted from the GLCM five feature second-order features namely auto-correlation, cross-correlation, entropy, contrast, and homogeneity are computed. A co-occurrence matrix calculates the likelihood of pixel values appearing in the angular direction as degrees (0, 45, 90, and 135) [11].

The statistical parameters such as mean, standard deviation, Energy, Contrast, Entropy, Homogeneity and Correlation are computed from the co-occurrence matrix and given in equations 1 to 11.

$$Mean = \mu_I = \sum_{j=0}^{N-1} \sum_{i=0}^{N-1} iK_{i,j} \tag{1}$$

$$\text{Standard Deviation} = \sigma_I = \sqrt{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} K_{i,j}\ (i-\mu_I)^2} \tag{2}$$

The energy (E) calculates the local invariability of the intensity levels. That is, high values of E indicate the distribution of the grey level values in the image is constant or periodic. The Contrast measures the quantity of course texture

$$Energy = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} k_{i,j}^{2} \tag{3}$$

$$Constract = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} K_{i,j}(i-j)^2 \tag{4}$$

$$Entropy = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} K(i,j)\ln[K(i,j)] \tag{5}$$

$$Homogenity = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} K(i,j)/1+(i-j)^2 \tag{6}$$

$$Correlation = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} K(i,j)[(i-\mu_x)(j-\mu_y)]/\sigma_x\sigma_y \tag{7}$$

LBP is an effective pattern-based method for describing the local texture pattern of the input image. The Local binary pattern operates in a 3*3 matrix block size, in which the center pixel is generated by thresholding values into binary zeros and ones, and then the center pixel value is compared with the 8 neighboring pixels one by one, assigning 0's and 1's.The advantage of combining GLCM and LBP is to obtain better feature values.

## 2.3 Classification

The extracted features are classified by combining machine learning algorithms such as Multi-Support vector machine Multi-SVM) and K-Nearest Neighbor (K-NN).

### a) K-NN Classifier

K-Nearest Neighbor is one of the simplest Machine Learning algorithms based on Supervised Learning technique. It stores all the available data and classifies a new data point based on the similarity. If any new data appears then it can be easily classified into a well suite category by using K- NN algorithm. It is a non-parametric algorithm, which means it does not make any assumption on underlying data. With the help of K-NN, we can easily identify the category or class of a particular dataset.

- Select the number K of the neighbors
- Calculate the Euclidean distance of K number of neighbors
- Take the K nearest neighbors as per the calculated Euclidean distance.
- Among these k neighbors, count the number of the data points in each category.
- Assign the new data points to that category for which the number of the neighbor is maximum.

### b) MSVM Classifier

An MSVM model is basically a representation of different classes in a hyper plane in multidimensional space [12]. The hyper plane will be generated in an iterative manner by MSVM so that the error can be minimized. The goal of MSVM is to divide the datasets into classes to find a maximum marginal hyper plane (MMH).Data points that are closest to the hyper plane is called support vectors. This algorithm is implemented with kernel that transforms an input data space into the required form. It converts non-separable problems into separable problems by adding more dimensions to it. It makes MSVM more powerful, flexible and accurate. Radial Basis Function (RBF) Kernel is employed in this work.

It maps input space in indefinite dimensional space. It is mathematically given by

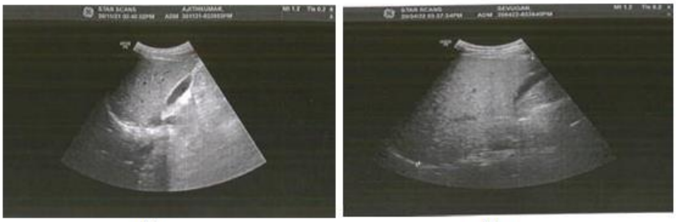
$$\mathrm{K}(\mathrm{x}, \mathrm{xi}) = \exp(-\mathrm{gamma}\ \mathrm{x} * \mathrm{sum}(\mathrm{x} - \mathrm{xi}\text{^}2)) \qquad (8)$$

Here, gamma varied from 0 to 1. Default value of gamma is 0.1.MSVM is a supervised learning algorithm that tries to find the hyper plane between different classes in an n-dimensional space. KNN algorithm makes high accurately predictions at the training phase just stores the dataset and when it gets new data, then it classifies that data into a category that is much similar to the new data. The Advantage of combining SVM with KNN is that SVM measures a large number of values whereas KNN accurately measures point values.

## 3. Experimental Results

### *3.1 Dataset*

For the experimentation, the real datasets are collected from the STAR scan and KGS scan center, Madurai. The datasets provided here are from the affected patients and the unaffected ones shown in Fig 1 &2 respectively.

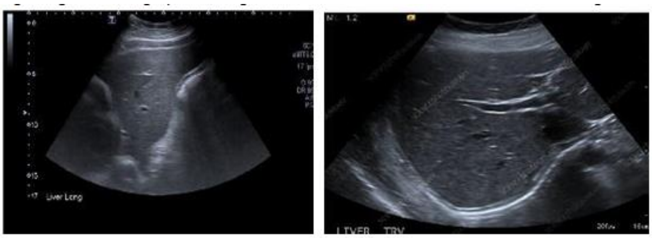


(a) (b)

Figure1. Input Images (a) data set 1 (b) data set 2

### *3.2 Qualitative Results*

The primary stage of pre-processing is noise filtering, the image resizes, and grayscale conversion. Filtering is done using a Gaussian filter it's a low pass filter that reduces the noise. The filtered image is resized into 256*256 pixels. The resized images are converted into a grayscale image for easier extracting the values. Fig. 2 represents the filtered images.



(c) (d)

Figure 2. Preprocessed Image of (c) data set 1 (d) data set

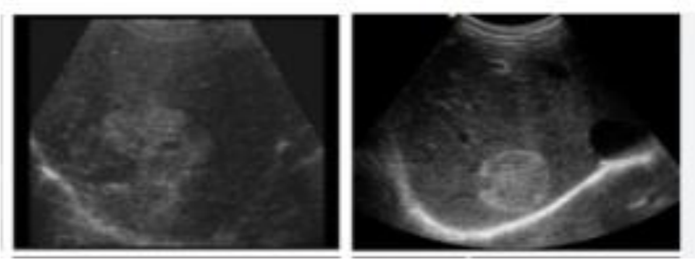


Figure 3. LBP features of (a) data set 1 (b) data set 2

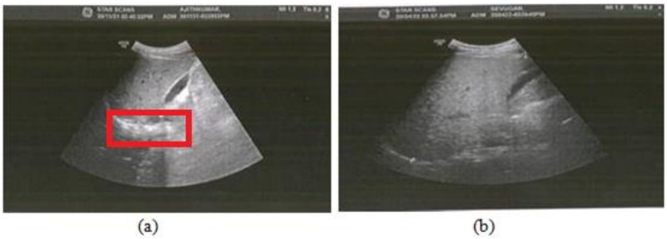


Figure 4. Classified Images of (a) data set 1 (b) data set 2

The Gaussian filter removes the noise present in the image. From the preprocessed image, GLCM and LBP features are extracted which is shown in Fig.3. The extracted features are classified by the combination of K-NN and MSVM classifier. In data set1, the tumor is identified and marked by red color rectangle. Whereas, in dataset 2 , nothing is marked which indicates that the image does not have any tumor.

Performance measures are a part of every machine learning technique. The following four metrics are calculated to find the performance of the proposed method.

### *Accuracy(A):*

A test's accuracy is defined as its ability to correctly distinguish between patient and healthy cases. To estimate the accuracy of a test by calculating the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \quad (9)$$

Where, TP- True Positive; TN-True Negative

FP-False Positive; PN-False Negative

### *Sensitivity(SE):*

A test's specificity is its ability to correctly identify healthy cases. Sensitivity can be estimated from the proportion of true positive inpatient cases. Mathematically, this can be stated as:

$$\text{Sensitivity} = (\text{TP}) / (\text{TP} + \text{FN}) \quad (10)$$

### *Specificity(SP):*

True negatives in healthy cases are used to find the specificity. Mathematically, this can be stated as:

$$\text{Specificity} = (\text{TN}) / (\text{TN} + \text{FP}) \quad (11)$$

### *Precision(P):*

Precision is the number of correct positive predictions divided by the total number of positive predictions. It is also called a positive predictive value (PPV) and it is given by

$$\text{Precision} = (TP) / (TP + FP) \qquad (12)$$

The calculated parameters are given in Table.1. From the table, it is observed that the combinations of K-NN and MSVM classifier performance are good when compared to the performance of the individual classifiers.

Table 1. Performance Evaluation of Proposed Method

| **Methods** | **Dataset 1** | | | | **Dataset 2** | | | |
|---|---|---|---|---|---|---|---|---|
| | **A** | **SE** | **SP** | **P** | **A** | **SE** | **SP** | **P** |
| K-NN | 80.26 | 81.79 | 82.23 | 79.89 | 81.37 | 80.72 | 81.33 | 78.98 |
| MSVM | 89.46 | 90.59 | 88.51 | 87.56 | 88.52 | 87.29 | 85.57 | 86.13 |
| Proposed Method (MSVM+ K-NN) | 92.30 | 91.72 | 90.47 | 91.13 | 91.89 | 90.12 | 89.47 | 90.54 |

From the above table A-represents the Accuracy, SE-represents the sensitivity, SP represents the Specificity, P represents the Precision.

K-NN classifier is easy to implement and more robust to noise. This method requires more training data. Even though, it performs well, computation cost is high because of calculating the distance between the data points for all the training samples.

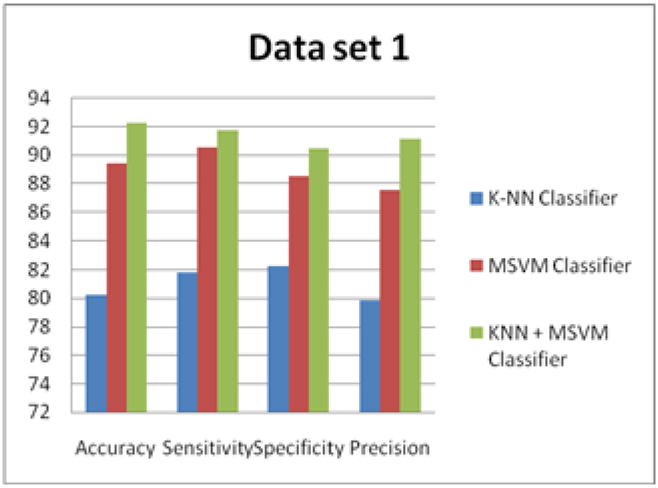



Figure5. Performance Comparison of Data set 1

MSVM uses the concept of margins and tries to maximize the differentiation between multi classes. It reduces the chances of model over fitting, making the model highly stable. It has high computation speed. When, we combining K-NN with MSVM, the classification accuracy get improved.

The Fig.5 & 6 shows the computed performance parameters of data set 1 & 2. From the graph, it is observed that the classification accuracy is improved for the combination of K-NN and MSVM classifier.

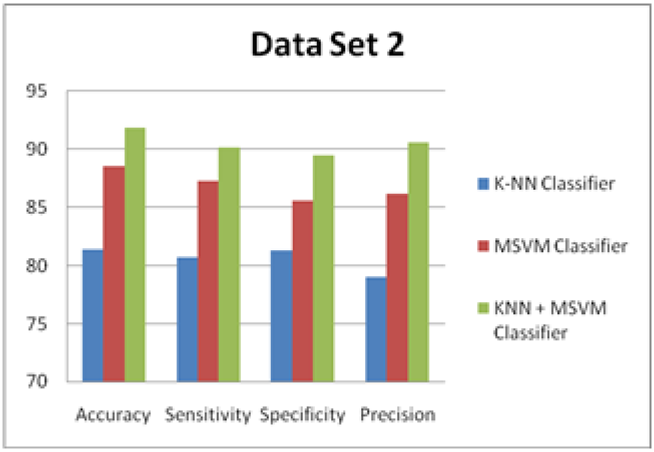



**Figure 6.** Performance Comparison of Data set 2

## 4. Conclusion

In this paper, machine learning based early stage identification of liver tumor using ultrasound image is proposed. Initially, the ultrasound images are preprocessed. Then, feature extraction algorithms such as GLCM and LBP are applied to get more efficient feature values. Machine learning algorithms such as Multi-SVM and K-NN classifiers are combined for the identification of liver tumor. Based on the above results and discussion, it is concluded that the aforementioned machine learning algorithms outperform the existing methodology.

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## Conflict of interest

The Authors have no conflicts of interest to declare that they are relevant to the content of this article.

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