International Journal of Computer Sciences and Engineering Open Access
Survey Paper Vol.-7, Special Issue-16, May 2019 E-ISSN: 2347-2693

Pre-processing and Classification of Prostate Images for Cancer Detection: A Survey

Swetha.P.C[1*], Mohan G Kabadi[2], Srivinay[3]

[1,2,3]Dept. of Computer Science, School of Engineering, Presidency University, Bangalore, India

**Corresponding Author: swethapc.reddy@gmail.com Tel.: 7090561612*

DOI: https://doi.org/10.26438/ijcse/v7si16.9397 | Available online at: www.ijcseonline.org

Abstract— In the recent years, prostate cancer has become the major cause of deaths in the male population around the world. Numerous computer aided techniques such as, Computer Aided Diagnosis (CAD) systems have been designed in order to detect prostate cancer. The CAD systems majorly consist of four stages namely preprocessing, segmentation, feature extraction and finally the classification stages that are interdependent on one another. The CAD systems perform the analysis based on the various screening techniques such as X-Ray, CT scans, TRUS images, MRI scan, and mp-MRI scans. Though the existing CAD systems are considered feasible, the major research challenge is in improving the accuracy, specificity, speed and usability of the existing CAD systems. This paper presents a survey on the various methodologies used for detecting the prostate carcinoma using various types of screening images.

Keywords— MRI(Magnetic Resonance Imaging), TRUS (Trans rectal Ultrasound), mp-MRI (Multi parametric-Magnetic ResonanceImaging***)***.

I. Introduction

Prostate cancer (PCa) is the most commonly occurring cancer in men, and its related mortality rate is second highest after lung cancer[21]. It is estimated that one in every seven men get affected by prostate cancer in their lifetime. Latest statistics show that the number of new prostate cancer cases worldwide in the year 2018 is about 1,276,106 and the number of deaths due to this cancer is about 358,989. Propitiously, there is a cure for prostate cancer if it is diagnosed at an early stage.

Prostate is a small, soft gland about the size of a walnut that is present below the bladder near the rectum in the male reproductive system [29]. Prostate cancer occurs when a normal prostate cell becomes abnormal which starts to grow and reproduce uncontrollably without having the signals to stop the typical cell growth [30]. In many cases, prostate cancer is a slow growing cancer that usually does not spread beyond the prostate gland. But once the cancer grows beyond the prostate gland, the survival chances of the patient decreases drastically. For this reason, detection of prostate cancer at an early stage where the cancer is still in the prostate gland is the key to provide absolute cure to this cancer.

Several traditional methods are used to detect prostate cancer such as, Digital rectal examination (DRE) where the doctor manually examines the gland through the rectum, where the doctor can feel the size and shape of the gland. If there is any abnormalities found in the test then the patient subsequently undergoes another test called as prostate specific antigen (PSA) test. But the DRE test can only detect any abnormalities in the back wall of the prostate gland and any abnormalities present in the front wall or the centre of the prostate gland cannot be diagnosed [27].

PSA is a glycoprotein found in the blood. High levels of PSA indicate the presence of prostate cancer. Usually it is said that higher the levels of PSA, greater are the chances of having prostate cancer. But the high levels of PSA may also be due to other reasons such as hormonal imbalances due to some medications, some minor infections or also due to the growing age of a person.

Hence, the DRE along with PSA test alone cannot accurately diagnose the cancer. Instead these tests commonly lead to either over diagnosis or under diagnosis of the patient, along with painful invasive methods such as biopsies which may lead to high possibilities of false positive or false negative results. In order to avoid such unnecessary issues and to accurately diagnose the prostate cancer, several computer aided diagnosis (CAD) systems started to develop.

In this paper we will look at the various steps involved in CAD system and we shall concentrate more on the various classification techniques that have been used for the detection of prostate cancer.

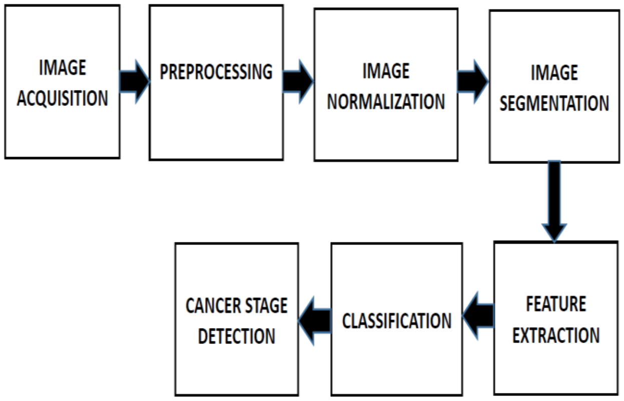

Figure 1: Typical CAD System for cancer detection

The figure 1 shows the various stages involved in a typical CAD system which are explained in detail in the sections to follow. The Table 1 shows the recent statistics of the prostate cancer cases in India, and their Mortality rates when compared to that of all types of cancers. This paper presents the overview of the different methods that have been used on different types of images.

Table 1: Statistics of cancer cases registered and mortality in India

Cancer Type	Level	India	Uttar Pradesh	Maharashtra	Karnataka
All kinds of Cancer	No. of cases registered	1117269	186638	102101	56330
	Mortality Rates	491597	82121	44924	24785
Prostate Cancer	No. of cases registered	37055	6454	3489	1882
	Mortality Rates	15562	2710	1465	791

II. PREPROCESSING

Once images are collected, they have to be cleaned for further analysis. Usually, the raw images contain noises that have to be removed and have unclear objects that may have to be enhanced. For this purpose a well-known image processing technique called image pre-processing has to be used for enhancing the quality of the image.

A. Filtering

Filtering is a pre-processing technique mainly used for suppressing either the high frequencies in the image(image smoothing) or the low frequencies (image enhancement/ edge detection).Anisotropic non-linear diffusion filtering[22] is a filter used for removal of noise in CT images by taking the edges of the image into consideration. Median filters[17][18] and high boost filters[17] can also be used for noise removal and to improve the image quality to ease the process of feature identification. Weiner filter[20] focuses on the removal of blur from the image caused due to some motion or unfocussed lens.

B. Contrast Stretching

The other name of contrast stretching is normalization which is a simple image enhancement technique to improve the contrast in an image by stretching the range of the intensity values. The stretching is performed by specifying the upper and lower pixel value limits on the image that has to be normalized.

For example, for an 8-bit gray level image the lower and upper limits are said to be 0 and 255. Let us consider the lower and upper limits to be named as a and b respectively. Then we can further consider the current lowest and highest pixel values to be c and d respectively [26]. Then each pixel is scaled using the equation,

$$P_{out} = (P_{in} – c)(b – a / d – c) + a$$

III. SEGMENTATION

Image segmentation can be said as the process of partitioning of an image into multiple segments. The main purpose behind performing segmentation is to simplify and convert the representation of a particular image into a form that is more meaningful and easier to analyze.

Image segmentation is specifically used to locate the objects and boundaries in an image, the outcome of which is group of segments when put togeather forms an entire image [24]. Prostate segmentation using edge detection techniques cannot be applied for Trans Rectal Ultrasound (TRUS) images due its low contrast, shadow region and also due to speckles. To overcome these drawbacks, Liu et al [8] made use of radial bass relief representation of image wherein, the original image was superimposed with the negative of the same image. Aarnink et al [2] made use of local standard deviation[28] to identify similar and dissimilar region in the images by using multidimensional framework.

Edge detection techniques again face challenges in MRI images due to the high soft tissue contrast. Samiee et al [6] made use of already existing information of the prostate shape in order to refine the prostate boundary[28]. Cootes et al [1] proposed a image segmentation for MRI images using Active Shape Model. Zhu et al [5] proposed a combination of two or three dimensional Active Shape Model.

Tang et al [3] for the first time used Active Shape Model to segment the CT images.

IV. FEATURE EXTRACTION

Analysis of images usually involves dealing with large amount of variables, which may in turn require huge memory space and computational power. Feature extraction methods help in reducing the number of resources required to describe a particular data set. S.S. Mohamed et al [7] made use of wavelet based approach for the diagnosis of prostate cancer in case of Trans Rectal Ultrasound (TRUS) images. The textural features were extracted from the images with the help of texture feature extraction filter. R. Manavalan et al [9] proposed a different approach for extracting features from a TRUS image where in Gray Level Run Length Matrix(GLRLM)was used to extract features from different direction of the segmented regions..

V. CLASSIFICATION

Image classification is basically the organization of data into categories. The obtained images are compared with the predefined database patterns in order to classify it into a proper category[12].

Duc Fehr [13] made use of t-Test Support Vector Machines wherein the features were selected through a two-sided and unpaired t-Tests. Recursive Feature Selection Support Vector Machines were also used to improve the performance of the classifier by finding the correlation between the features.

Mark A Sheppard [4] proposed a fast classification approach through Java Textural Analysis/Classification (JTAC) where the features were extracted using Haralicks textural features and clustered using Minimum Squared Error (MSE) clustering algorithm.

Gaussian Mixture Model (GMM) classifier was used by R.R. Wildeboer [23] which made use of multi parametric space in which a combination of abnormal distributions are computed to derive class specific data.

Islam Reda [24] proposed a classifier known as Non-negativity constrained auto encoder (NCAE) that gave superior reconstruction in deep networks by making use of encoded and decoded layers having negative weights.

Yujie Feng [25] used 3-D CNN (Convolutional Neural Network) which uniformly extracted the features both spatial as well as temporal in order to classify the samples as normal or cancerous.

VI. CONCLUSION

Early diagnosis of prostate cancer plays a crucial role in increasing the survival rate of a person. Efficient and effective CAD systems need to be developed in order to diagnose the cancer at an earlier stage. Table 2 shows the comparative study performed by different researchers and the results they have obtained.

Table 2: Summary of the methods, classifiers and performance metrics based on various studies

Authors	Methods	Classifiers	Results
Aaron Greenblatt, Clara Mosquera -Lopez, SosAgaian[11]	Analysis of image texture was made through quaternion wavelet transform and local binary patterns.	It used two classifiers a) Quaternion neural network. b) Binary Support Vector Machines	Accuracy – 98.87%
Clara.M.Mosqueera-Lopez and Sos.Agaian [10][11]	The features were analyzed based on wavelet energy distribution, color ratio based fractal dimensions	Support Vector Machines(SVM)linear kernel	Accuracy – 97%
Chuan-Yu Chang, Hui-Ya Hu, Yuh-Shyan Tsai [14]	Dynamic MRI images were segmented using Active Contour Model (ACM) and the features are selected through Fisher's Discrimination Ration	Support Vector Machines(SVM) classifiers were used	Accuracy – 94.749% Sensitivity – 90.466% Specificity – 96.612%
Yunjie Chen, Liangbin Zhang, Wenjun Ma, FenGao, Yunkai Zhu, Yaqing Chen [16]	Makes use of convex analysis of mixture with compartmental model (CAM-CM) where each pixel in the image as a weighted composition of unique tissues. The study was conducted on T2 weighted images and Diffusion weighted images.	Artificial Neural Networks(ANN-PT) were used as classifiers	Accuracy of T2 weighted images – 86.3% Accuracy of Diffusion weighted images – 84.2%
Islam Reda, Ahmed Shalaby, Fahmi Khalifa, et al [15]	The study was conducted on Diffusion weighted Magnetic Resonance Images (DW-MRI) [29]. Image segmentation was	Stacked non negativity constraint algorithm (SNCAE)	Accuracy – 100% Sensitivity – 100% Specificity – 100%

	done using level set method and a cumulative distribution function was used to differentiate between normal and affected tissues.		
Islam Reda, Ahmed Shalaby, Fahmi Khalifa, et al [15]	The study was conducted on DW-MRI images [29]. Image segmentation was done using level set method and a cumulative distribution function was used to differentiate between normal and affected tissues.	K-Star (K*) classifier	Accuracy – 94.3% Sensitivity – 94.3% Specificity – 94.4%
Islam Reda, Ahmed Shalaby, Fahmi Khalifa, et al [15]	The study was conducted on DW-MRIimages [29]. Image segmentation was done using level set method and a cumulative distribution function was used to differentiate between normal and affected tissues.	K- Nearest Neighbor (KNN) classifier	Accuracy – 88.67% Sensitivity – 88.6% Specificity – 88.7%
Islam Reda, Ahmed Shalaby, Fahmi Khalifa, et al [15]	The study was conducted on DW-MRIimages [29]. Image segmentation was done using level set method and a cumulative distribution function was used to differentiate between normal and affected tissues.	Random Forest Classifier	Accuracy – 86.7% Sensitivity – 86.8% Specificity – 86.8%
Islam Reda, Ahmed Shalaby, Fahmi Khalifa, et al [15]	The study was conducted on DW-MRI images [29]. Image segmentation was done using level set method and a cumulative distribution function was used to differentiate between normal and affected tissues.	Random Tree classifier	Accuracy – 84.9% Sensitivity – 85.1% Specificity – 84.9%
Ying Liu, Xiaomei An [19]	The study was made on 10056 DW-MRI images. [19]	Convolutional Neural Network (CNN) as a classifier	Accuracy – 80.15%
Islam Reda, Ahmed Shalaby, mohammed Elmogy,Ahmed Aboulfotouh et al [21]	Proposed a Computer aided diagnosis system to diagnose prostate cancer at an earlier stage using DW-MRI images acquired through different b-values.	Quadratic Discriminant Analysis (QDA) classifier	Accuracy – 77.8% Sensitivity – 84% Specificity – 70%
Islam Reda, Ahmed Shalaby, mohammed Elmogy,Ahmed Aboulfotouh et al [21]	Proposed a Computer aided diagnosis system to diagnose prostate cancer at an earlier stage using DW-MRI images acquired through different b-values.	Linear Discriminant Analysis (LDA)	Accuracy – 73.3% Sensitivity – 80% Specificity – 65%

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