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Computer aided diagnosis of cancer: A survey

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***Abstract*— This paper presents a survey of various medical imaging modalities used for imaging different types of cancers and the roles of Computer Aided Diagnosis (CAD) in diagnosing cancer. Developing an effective and efficient Computer-aided diagnosis system for all types of Cancer is a challenging task and also requires clinical research. It can be used to increase the survival rate of patients. For this purpose, various CAD systems have been scrutinized in a large number of research studies. Generally a CAD system for cancer diagnosis consists of the following computational steps: image acquisition & data collection, pre-processing, segmentation, feature extraction, and classification. This paper takes an attempt to describe various medical imaging modalities such as x-ray, ultrasound, computed tomography (CT), positron emission tomography (PET) and magnetic resonance imaging (MRI) available for imaging cancer. It also provides a brief description of various stages of CAD of cancer. Moreover, lung region segmentation of five CT lung images is implemented using K-Means algorithm, Fuzzy C-Means algorithm and Otsu method and the results are given.**

***Keywords*— Computer aided diagnosis, cancer, segmentation, feature extraction, classification.**

I. Introduction

Cancer is one of the deadliest diseases in which the cells grow uncontrollably. Cancer can be categorized into three types viz., carcinoma, sarcoma and leukemia. Carcinoma occurs from the epithelial cells which covers the human body by both internal and external surface. Examples of organs which are covered by such epithelial cells are lung, breast, and colon. Sarcoma is another type of cancer which grows from the cells of neighborhood tissues such as bone, cartilage, fat, connective tissue, and muscle. Leukemia is a type of cancer which generates in the blood cells of the bone marrow [1].

Cancer is caused by various internal and external factors namely inherited genetic mutations, hormonal problems, lack of immunity, tobacco consumption, smoking, infectious organisms, unhealthy diet, overweight or obesity, lack of physical work, poor nutrition [2]. Cancer can be prevented by avoiding smoking habit, increasing intake of more raw vegetables and fruits, utilizing the grain foods, avoiding meat and refined carbohydrates, retaining a healthy weight, exercising and reducing exposure to sunlight. Cancer is detected through screening tests or through medical imaging techniques [3]. Medical imaging techniques help in early detection and treatment of cancer. Image processing techniques have helped the clinicians to identify tumor region from medical images. Complete computer aided diagnosis system are also developed which combines image processing and machine learning techniques to accurately diagnose cancer from medical image.

This paper gives an overview of various stages involved in the CAD system for diagnosing the cancer. The rest of the paper is organized as follows. Section 2 gives an overview of various stages of CAD system for diagnosis of cancer. Section 3 concentrates on list of image databases available for cancer diagnosis. Section 4 presents the result and discussion of lung region segmentation using various image quality measures of segmented images. Section 5 presents the conclusion.

II. Overview of CAD system for diagnosis of cancer

The Computer-Aided Diagnosis (CAD) has been improved quickly in the last two decades. The prominent role of CAD system is used to interpret the medical images and also helps the radiologists in clinical decision making and various studies on CAD system and technology reveals that the CAD system provides accurate results to radiologists, reduces human workload [10]. CAD systems are developed by using various image processing techniques which are used to execute on images obtained from various medical imaging modalities and all types of examination.

The CAD system consists of the following computational tasks: image acquisition, preprocessing, segmentation, feature extraction and classification. Various medical imaging modalities can be used for image acquisition and data collection process. The role of preprocessing step is to remove the unwanted noise in an image background and to improve the quality of image in order to determine the focal areas in the image. The second step is image segmentation which divides the image into small portions and discriminates the regions of interest from the background. In feature extraction step, the features can be extracted for classification process and it measures the properties of segmented areas. Classification step determines whether the segmented region is benign or malignant and level of malignancy with the help of extracted features. The computational steps of CAD system are shown in Fig. 1.

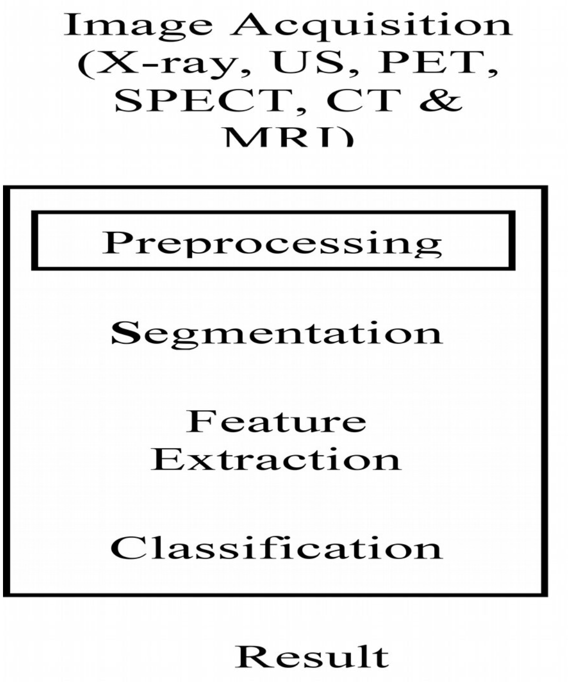

Fig. 1: Computational steps of CAD system

A. Image acquisition and preprocessing

The image acquisition is a prerequisite for image processing. One of the earliest medical imaging modalities is X-ray. X ... which can penetrate ... nerate an image c ... nd fluid distributi ... zes ultra-high-freq ... provide the cros ... It can distingui ... Magnetic resonanc ... imaging modalitie ... veals the internal ... muscles and the ... images without ... ay (CT), which is ... es three-dimensio ... zes solid body par ... , muscle tissue an ... ET) is a medical ... nensional picture o ... is widely used ima ... function. CAD he ... f images obtained ... ection of cancer ar ... ems may be slight ... 21, 23, 2 ...

Preproc ... eliminate t ... areas in t ... includes nucleus/cell segmentation for extracting the cellular-level information [4]. It can be used to improve the quality of image and to remove the unwanted regions. In this step the speckle noise reduction and image enhancement can be achieved simultaneously without destroying the image features of various cancer modalities for diagnosis. The important preprocessing techniques used in various CAD systems of cancer are shown in the Table I. An appropriate selection of the preprocessing techniques can improve the accuracy of CAD system.

B. Segmentation

Segmentation is an important phase and one of the toughest tasks in the medical image processing and pattern recognition. The medical image segmentation requires the division or separation of the image into non overlapping regions of similar attribute. The main objective of segmentation in medical image applications is to extract suspicious image features from the image data which helps to assist the pathologists for diagnosis [5]. Segmentation helps the CAD system to distinguish the various structures in the medical image, e.g. heart, lung, ribcage, possible round lesions and matching with anatomic databank. There are a number of techniques available for segmenting the medical image viz., boundary extraction, region growing, gray-level histogram thresholding, deformable models (snakes - active contour maps), and level set methods. The unavailability of ground truth image in the segmentation stage makes it difficult in the decision making by the CAD system since the CAD systems depend on the ground truth for making a comparison with expert pathologists. The ground truth is obtained from expert's opinions [13]. Segmentation algorithms are based on the intensity of the image, texture variations of the image, colors and shapes. The different segmentation methods applied for various types of cancer and their merits and demerits are summarized in Table II.

C. Feature Extraction

Feature extraction and selection are vital steps in cancer detection and classification. An optimum feature set must contain effective and discriminating features. In this phase, extracting the useful features and selection of good features are an essential task for CAD systems. The features of medical images can be classified into four types: texture, morphologic, model-based and descriptor features. The general strategies for choosing important features mainly considers: discrimination, reliability, independence and optimality. The combination of best performed features does not guarantee that the systems will work well and effectively. The aim of feature extraction and selection is to maximize the discriminating performance of the feature group [5]. The features used in various CAD systems for cancers are listed in

TABLE. I. AN OVERVIEW OF PREPROCESSING TECHNIQUES USED IN CAD SYSTEMS.

Type of cancer	**Category of noise**	**Methods**	**References**
Breast cancer	Speckle noise	Wavelet transform: Low pass filter and high pass filter, Curvelet transform: Unequispaced FFT method. Histogram equalization and median filtering.	[8], [38]
Prostate cancer	Speckle noise	Median filter and statistical based normalization.	[32]
Cervical cancer	Speckle noise	Linear filter: Low pass filter, Otsu thresholding, median filtering , mean-shift filtering method and canny edge detection method.	[15],[18]
Ovarian cancer	Speckle noise	Wavelet decomposition and wavelet thresholding technique.	[16]
Lung cancer	White noise	Denoising algorithm: Gaussian smoothing model, wiener filter and nonlinear anisotropic diffusion filter.	[20],[33]
Brain tumor	Speckle noise	Median filter, Brain surface extractor (BSE) algorithm and anisotropic diffusion filter.	[36],[37]

TABLE II. A SUMMARY OF SEGMENTATION TECHNIQUES USED FOR CAD OF CANCER AND THEIR MERITS AND DEMERITS.

Type of cancer	**Methods**	**Merits**	**Demerits**	**References**
Breast cancer	Level set methods: Spatial fuzzy clustering (SFC), Improved region growing (RG), Cellular neural network (CNN), Memetic algorithm(MA) and Artificial neural network (ANN).	Provides more accurate and robust segmentation.	-	[38]
Prostate cancer	Supervised learning methods: Support vector machine (SVM) and Relevance vector machine (RVM). Unsupervised learning methods: Markov random fields (MRF) model fuzzy segmentation. Candidate segmentation and the Imorphic's algorithm and ScrAutoProstate's algorithm.	Supervised methods enhance the accuracy of the prostate cancer localization. Candidate segmentation is used to emphasize the suspected area in the prostate glands.	To find the value of optimal weighting factor is difficult in supervised methods.	[17], [32]
Cervical cancer	Level Set method, Adaptive fuzzy k-means thresholding (AFKM) method	Detects the pre-cervical cancer stage.	-	[18], [39].
Lung canc				
Brain tum				
Skin cance				

TABLE III. FEATURE EXTRACTION AND SELECTION METHODS USED IN VARIOUS CAD SYSTEMS FOR CANCERS

Type of cancer	**Category of feature**	**Characteristics**	**Reference s**
Breast cancer	Wavelet and curvelets features. Statistical features and Texture features: Histogram based approach, mean, variance, standard deviation and entropy. Intensity histogram features, Gray level co-occurrence matrix (GLCM) features, Region features and shape measurements.	The mentioned features are used to extract the object shape accurately and used to differentiate the benign and malignant tumor of breast.	[8], [19], [38]
Prostate cancer	Pharmacokinetic features: maximum uptake (MU), time to peak (TTP), wash-in rate (WI), washout rate (WO), area under the curve S(t) (AC), and area under the curve S(t).	Tofts pharmacokinetic model provides the interaction details of contrast agent and soft tissue. It suffers from complexity due to the need of conversion from MR signal intensities into contrast agent concentration.	[34]
Cervical cancer	Geometric features (GF): the funnel area. Cervical cell features: nucleus size, cytoplasm size, nucleus' grey level and cytoplasm's grey level	It is used to specify an exact location of the internal cervical os.	[15], [39]
Ovarian cancer	Morphological features: Shape, size, solidity, vascularity and total number of cavities present in tumor. ovarian wall thickness, inner wall structure, and presence of septa and papillaries. Vascular features: Pulsatility index, resistance index, time-averaged maximum velocity, presence of diastolic notch, and vessel location. Texture features: Intensity, regularity, coarseness, contrast, homogeneity.	Morphological features are used to differentiate the benign and malignancy of ovary.	[35]
Lung Cancer	Morphological feature and spatial histogram. Texture feature, shape and appearance of lung nodules: Calcification patterns, internal structure, lobulation, margin, sphericity, spiculation and texture.	The mentioned features are used to detect the highly suspected malignant nodules of lungs and provide the region boundaries of lungs.	[9], [40]
Brain tumor	Intensity feature, Texture based features: local binary patterns (LBPs) and gray level based features. Gray level co-occurrence matrix (GLCM) features: contrast, correlation, energy and homogeneity. Wavelet feature and Law's energy texture feature.	GLCM features are used to distinguish the normal tissue from the abnormal tissue of brain and also used to find the texture pattern of an image.	[37]

TABLE IV. A SUMMARY OF VARIOUS CLASSIFIERS USED IN CAD SYSTEMS FOR CANCER

Type of cancer	**Category of classifier**	**Features used**	**References**
Breast Cancer	Artificial neural network (ANN), random forest, naïve Bayes, K-nearest neighbor (KNN) and Support vector machine (SVM) classifier.	Intensity histogram features, shape, text features, wavelets and curvelets features.	[8], [38]
Prostate Cancer	Large margin classifier and Support vector machine (SVM) classifier.	Anatomical and pharmacokinetic features.	[32], [34]
Ovarian Cancer	Decision tree (DT), fuzzy Sugeno, k-nearest neighbor (KNN), probabilistic neural network (PNN), and support vector machine (SVM).	Morphological features, vascular features and texture features:	[35]
Lung sCancer	Rule based classifier and Support vector machine (SVM) classifier.	Texture features, shape and appearance of lung nodules.	[40]
Brain tumor	An adaptive neuro fuzzy inference system (ANFIS) classifier which combines neural network and fuzzy logic and seed point selection method.	Texture features, intensity feature and Gray level co-occurrence matrix (GLCM) feature.	[37]

D. Classification

After completing the feature extraction and selection process, the results are passed as input into a classifier to categorize the medical image regions into normal/abnormal tissue or lesion/non-lesion or benign/malignant classes. Most of the articles concentrate on the classification of malignant and benign lesions which is commonly referred as lesion classification, and some of the publications give importance on classifying lesion and non-lesions which is known as lesion detection, and very few of them focus on both lesion classification and lesion detection. Lesion detection is mandatory step for lesion classification. The summary of various classifiers used in CAD systems for cancer are shown in Table IV.

III. DATASETS AVAILABLE FOR CANCER

Various databases of cancer images are available for researchers in the field of medicine and engineering in addition to clinicians. Table V provides some of the available medical imaging databases for cancer [14].

The segmented results are compared using Mean Square Error (MSE), Peak Signal to Noise Ration (PSNR), Structural Similarity Index Matrix (SSIM) and Normalized Cross Correlation (NCC) [29]-[31]. Table VI gives these performance measures on the five CT lung images. It can be inferred from the results that for the given five lung images FCM performs based segmentation is better than the other methods.

TABLE V. AN OVERVIEW OF VARIOUS MEDICAL IMAGE DATABASES.

Name of the Repository	**Organ**	**Imaging Modality**	**References**	**Register to view**
Lung Image Database Consortium (LIDC)	Lungs	CT	http://imaging.cancer.gov/programsandresources/InformationSystems/LIDC	No
Early Lung Cancer Action Program (ELCAP)	Lungs, heart, abdomen, liver, spine	CT,DICOM	https://eddie.via.cornell.edu/cgi-in/datac/ signon.cgi	Yes
National Biomedical Imaging Archive (NBIA)			https://wiki.nci.nih.gov/display/CIP/NBIA+at+CBIIT+Image+Collections	No. (login is required when the downloaded data size is 3Gb)
Database1: CT Colonography (CTC)	-	CT		
Database 2: FDG-PET Lymphoma	Lymphoma cases	PET,CT		
Database 3: Head-Neck Cetuximab (RTOG 0522 and ACRIN 4500)	Head and Neck	PET, CT, RTSTRUCT, RTDOSE		No
Database 4: IDRICONDUIT	-	DX, CT, CR		
Database 5: I-SPY	Breast,	MRI, HC		
MEDPIX	Ear, Lungs, Chest and Thorax, Prostate, Liver, Skull and Content, face and neck	CT, PET, MRI and CR	http://rad.usuhs.edu/medpix/parent.php3?mode=default#to	No

IV. IMPLEMENTATION RESULTS OF LUNG CANCER SEGMENTATION

In this work we have performed segmentation of lungs in five CT images using K-Means Method, Fuzzy C Means Method and Otsu Method [25]-[28]. These images are collected from a hospital. Fig. 2 shows a sample lung image along with the resultant segmented images.

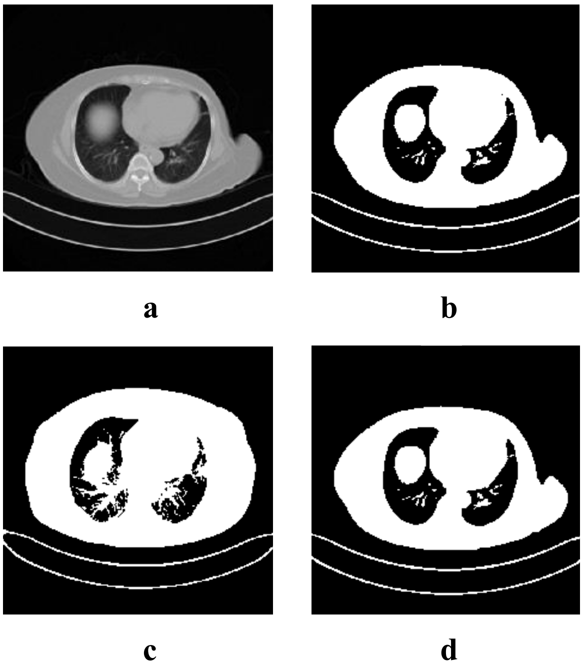

Fig 2. Results of segmentation (a) Original Lung image (b) K-Means Method (c) Fuzzy C Means Method (d) Otsu Method

TABLE VI. COMPARATIVE RESULTS OF VARIOUS PERFORMANCE MEASURES FOR LUNG IMAGES

Image	Segmentation Method	MSE	PSNR	SSIM	NCC
Image 1	K Means	2.004	69.228	0.781	0.9559
	FCM	**0.336**	**77.029**	**0.956**	**0.9559**
	Otsu	2.004	69.229	0.781	0.9559
Image 2	K Means	1.933	69.406	0.788	0.9524
	FCM	**0.306**	**77.389**	**0.960**	**0.9524**
	Otsu	1.924	69.405	0.788	0.9524
Image 3	K Means	2.073	69.084	0.775	0.9529
	FCM	**0.355**	**76.746**	**0.953**	**0.9529**
	Otsu	2.071	69.086	0.775	0.9529
Image 4	K Means	1.856	69.560	0.793	0.9649
	FCM	**0.285**	**77.722**	**0.9624**	**0.9649**
	Otsu	1.857	69.560	0.7934	0.9649
Image 5	K Means	1.689	69.972	0.8078	0.9650
	FCM	**0.228**	**78.674**	**0.9699**	**0.9650**
	Otsu	1.688	69.973	0.8078	0.9650

V. CONCLUSION

This paper gives an overview of recent works in CAD of cancer, various types of cancer and various imaging modalities available for the diagnosis of cancer. A general overview of various stages of CAD for cancer viz., pre-processing, segmentation, feature extraction and classification is given. Various methods available in literature for these stages are also reviewed and a comparison of their advantages and disadvantages is given. Apart from this, segmentation using FCM, K-means and Otsu is carried out on five CT lung images and the results are given.

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