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Subject Review: Diagnoses cancer diseases systems for most body's sections using image processing techniques

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Abstract

Medical imaging has become an important part of diagnosing, early detection, and treating cancers. In this paper, a comprehensive survey on various image processing techniques for medical images specifically examined cancer diseases for most body sections. These sections are Bone, Liver, Kidney, Breast, Lung, and Brain. Detection of medical imaging involves different stages such as classification, segmentation, image pre-processing, and feature extraction. With regard to this work, many image processing methods will be studied, over 10 surveys reviewing classification, feature extraction, and segmentation methods utilized image processing for cancer diseases for most body's sections are clearly reviewed.

Keywords: Feed-Forward Back Propagation NN; A gray-level co-occurrence matrix (GLCM); Dense Scale Invariant Feature Transform (DSIFT); Deep convolutional neural network (DCNN).

1. Introduction

The human body is made up of several types of cells. There are various tumor types with different characteristics that are often observed in the human body. Globally, cancer is considered to be a deadly disease. The medical image processing technique for the diagnosis of an important disease is considered vital for human life. Medical imaging can be defined as the method and process to create visual representation regarding the body's interior for medical intervention and clinical analysis, also the visual representations related to the functions of a few tissues (physiology) or organs [1]. The image technologies have various types, including ultrasonography, X-ray imaging, computed tomography (CT), biopsy imaging, optical coherence tomography, and magnetic resonance (MR) images were majorly utilized in the clinical diagnosis for many disease types. Also, efficient medical images might be of high importance to aid in treatment and diagnosis; they might also be significant in the domain of education for health-care students through explaining with such images help them in their study [2]. The list of images in figure (1) represents the CT-scan and MRI images for most body's sections (Bone, Breast, Kidney, Liver, Lung, Brain in two states (abnormal, normal) that are used in different researches in this subject review [3].

The remaining part of this study is organized in the following way. Section II Literature Survey, discussing the extensive review of existing research towards the diagnose of cancer diseases for most body's sections and its classification. Section III Comparative study of different cancer diseases for most body's sections using image processing techniques, that are dealing with a comparative analysis of various discussed techniques is provided. In section, IV summarizes and concludes the paper.

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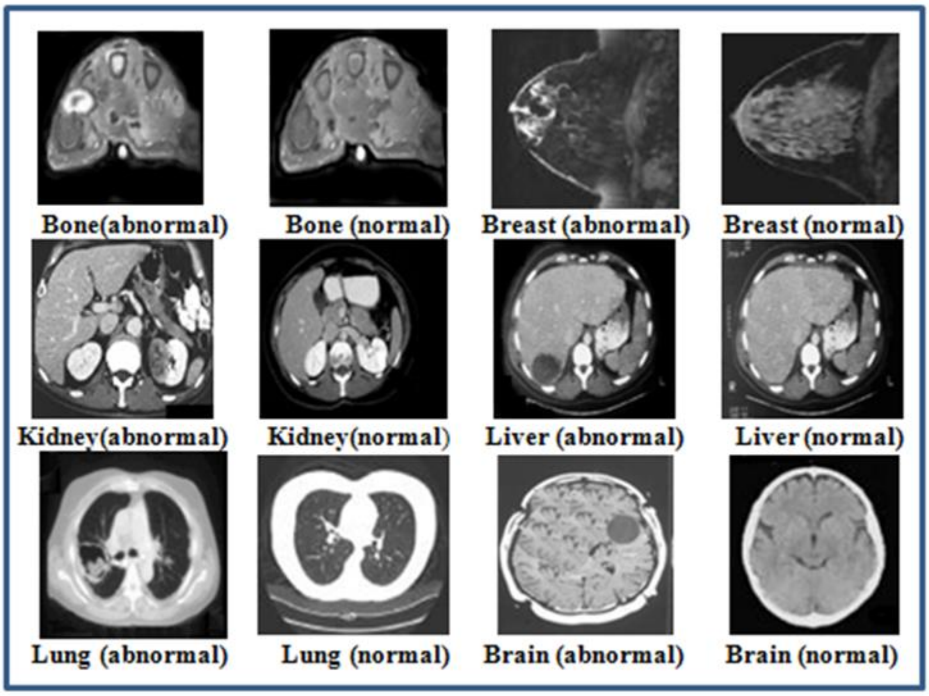

Figure 1 Images for Different Cancer Diseases for Most Body's Sections.

2. Literature survey

Kalpana U. et al. [4] In this study, the ANN approach is provided; it is referred to as feed-forward backpropagation NN for classifying MRI into timorous and normal MRI. The technique of image processing helps to detect tumors in MRI feature extraction from a gray-level MRI with the use of a gray-level co occurrence matrix (GLCM). NN works in 2 modes; the first one is learning/training, whereas the other one is recognition/testing. B.Balakumar et al. [5] In the suggested system, initially, the self organizing map NN trains the features which are extracted from the discrete wavelet transform (DWT) blend wavelets, whereas the subsequent filter factors were trained via KNN, and the process of testing also was done in 2 phases. The suggested classification system is classifying the tumors of the brain in double-training process, providing adequate performance over conventional classification techniques. Furthermore, the classifiers might be classifying (accurately) the brain image status into abnormal/normal. Bal et al. [6] In this study, a method for automated brain tumor segmentation was suggested with the use of rough fuzzy C-means as well as shape-based topological properties for quantifying the tumor region. In addition, the patch-based K-means approach was carried out for skull stripping (extraction of brain tissue) as pre-processing step. In addition, the benefit of utilizing RFCM over conventional FCM and HCM is that it might be accurately handling the overlapping partitions and uncertainty in datasets. Also, RFCM's execution time is decreased with the suggested centroids initialization technique. The suggested approach is effectively utilized to standard benchmark datasets for automatically predicting and segmenting the regions of brain tumors. In the suggested approach, the quantitative analysis indicates a significant performance compared to previous most up to date algorithms in terms of ground truth (manual segmentation). MZ.Zafar et al. [7] The suggested technique includes 3 stages for determining the existence of brain tumors. An input image (RGB) was converted into gray-level one, whereas the skull has been stripped with the use of image masking in the phase of pre-processing. With regard to 2nd stage, features were extracted with the use of geometrical descriptors. In addition, such geometrical descriptors consist of 3 geometrical shapes, hyperbola, parabola, and eclipse. Also, the performance regarding such geometrical shape descriptors was assessed by means of Local Quinary Patterns (LQPs) and Local Ternary Pattern (LTPs). KNN and SVM classifiers were utilized to classify the MR Images into the unhealthy and healthy brain. Also, experiments were achieved on Kaggle brain MR Imaging dataset, whereas the results were put to comparison with current approaches. The experimental results are showing that the parabola descriptor achieves 97.5% in comparison to other geometrical shape descriptors such as hyperbola and eclipse. Mohsin Jadoon M et al. [8] This study suggested a classification related to mammograms for the detection of breast cancers on the basis of MLP and DCT. In addition, the mammogram patches were initially filtered via Column wise neighborhood operations Filter (COLFILT). Furthermore, improved patches were divided into 4 subbands with the use of DCT. The approach of Dense Scale Invariant Feature Transform (DSIFT) is used for extracting the 6 rotation as well as scale invariant features with regard to all subbands. Through the use of such subbands regarding all patches, the feature matrix was more processed through MLP for classification. Nadeem Tariq

[9] suggested a system with the goal of designing a Computer-Aided Diagnosis (CAD) system for distinguishing between malignant (cancerous) and benign (non cancerous) mammogram. The diagnosis accuracy of radiologists was increased when using CAD. The texture features from the mammogram have been evaluated with the use of GLCM along 0°, for the calculated features, the major efficient ones with large contributions for achieving the required output have been selected and applied to ANN for classification and training since ANN was majorly used in many fields including, medical diagnosis, pattern recognition, machine learning, etc. In this study, a mini MIAS database was utilized, whereas overall sensitivity, accuracy, and specificity achieved with the use of the suggested system were 99.3%, 99.4%, and 100%. Dina A. Ragab et al. [10] This study introduced a new method to classify breast cancers with the use of deep learning as well as a few segmentation approaches. A novel CAD system was suggested to classify malignant and benign mass tumors with regard to the breast mammography images. There are 2 approaches to segmentation in the suggested CAD system. The first one includes indicates manually specifying the region of interest (ROI), whereas the other applies the method of region and threshold based. In addition, the deep convolutional neural network (DCNN) was utilized in feature extraction. Furthermore, the last fully-connected (fc) layer was connected to SVM for obtaining excellent accuracy. Asuntha A1 et al. [11], This paper proposes an approach for detecting bone cancer in MR images with the use of medical image processing techniques. A proposed approach has some pre-processing techniques which use Gabor filter to smoothen the image and remove the noise from an image. The segmentation is carried out by using superpixel segmentation and multilevel segmentation. This methodology is used for identifying bone cancer by various pre-processing techniques like filtering and gray conversion. After filtering, edge detection and morphological operations are applied. In 2nd stage, superpixel segmentation was achieved, and some of the important features have been extracted from images. After that, the extracted features were utilized for identifying the bone cancer; such features were utilized for training and testing NN. The suggested system is effectively detecting bone cancer from CT scan images. Also, the system is achieving its expectation at the end of the system. Sonal S. Ambalkar1 et al. [12] This study suggested a tumor detection method with the use of machine learning, while the MRI images are the dataset for performance analysis. Bone tumor detection is the main focus of this work. The algorithm was conducted in openCV to make the system more convenient and faster. Eftekhar Hossain et al. [13] To detect bone tumors, this work applies a connected component labeling algorithm. ANN was utilized to classify the bone tumors. In addition, a total of 220 bone MR images related to previously-verified patients were obtained, while such images' texture features were utilized for the testing and training of NN. Furthermore, the acquired performance regarding the classification results is showing that NN is providing a success rate of 92.50% in the bone tumor classification. Amita Dasa et al. [14] This study suggested a new system referred to as the technique of Watershed Gaussian-based Deep Learning (WGDL) for effectively delineating the cancer lesion in the liver's CT images. Overall, 225 images have been utilized in the presented study for developing the suggested model. At first, the liver has been separated with the use of marker controlled watershed segmentation process, and lastly, cancer affected lesion is segmented with the use of GMM algorithm. Following tumor segmentation, many texture features are extracted from the segmented region. In addition, such segmented features have been fed to the DNN classifier with regard to automated classification of 3 liver cancer types, for instance, metastatic carcinoma (MET), hepatocellular carcinoma (HCC), and hemangioma (HEM). Hüseyin Kutlu et al. [15] This study suggested a new brain and liver tumor classification approach with the use of CNN in feature extraction, DWT in signal processing, and LSTM in signal classification. The method used in this work (CNN-DWT-LSTM) is used for classifying the CT images related to livers with tumors as well as classifying MR images regarding the brains with tumors. The suggested approach is classifying the liver tumor images as malignant or benign and, after that classifying the brain tumor images as the pituitary, glioma, and meningioma. Ali Muhamed Ali et al. [16] This study suggested ML method to classify the kidney cancer sub-types with the use of miRNA genome data. Also, by using empirical studies, it was identified that a total of 35 miRNAs having unique key features aiding in kidney cancer sub-type diagnosis. Neighborhood Component Analysis (NCA) was utilized for extracting the discriminative features from miRNAs, and LSTM, a type of recurrent NNs, was used for classifying certain samples of miRNA into kidney cancer subtypes. Furthermore, just a couple of kidney sub-types were taken into account for classification. Goran Jakimovski et al. [17], In this study, scans of CT has been utilized for the training of a regular CDNN and a double convolutional Deep Neural Network (CDNN). Those topologies have been tested against the images of lung cancer for the determination of Tx cancer stage where those topologies have the ability of detecting the likelihood of lung cancer. The initial step has been the pre-classification of the CT images from initial data-set so that the CDNN training may be focused. After that, the double CDNN has been built with the max pooling for the purpose of performing a more detailed study. Ultimately, CT scans of a variety of the Tx lung cancer stages have been utilized for the determination Tx stage where CDNN would be capable of detecting the likelihood of lung cancer. The regular CDNN has been tested against the proposed double CDNN. Utilizing this algorithm, the doctors can have additional help in the early detection of lung cancer as well as its early treatment. Following a detailed training with 100 epochs, the maximum accuracy that has been obtained was 0.9962, while regular CDNN could only obtain 0.876 accuracy. Talha Meraj , et al.[18], In this study, the authors have proposed a model for the precise detection lung cancer through classifying it into malignant and benign nodules. Several approaches, which include the filtering and noise removal have been implemented for the stage of the preprocessing. As a result, OTSU and semantic segmentation have been utilized for the accurate detection of unhealthy nodules of the lungs. There have been totally, 13 nodule features

obtained with the use of the PCA approach. There have been 4 optimum features chosen according to the efficiency of the classification. In the stage of the classification, there have been 9 different classifiers utilized in addition to 2 validation scheme types, in other words, the train test holdout validation with a 70-30 data split as well as a 10 fold cross-validation. The experimentations of this study have shown that the suggested system had provided a 99.23% accuracy with the use of the logic boost classifier.

3. Comparative analysis of different cancer diseases systems

Table 1 will explain the comparison between previous systems.

Table 1 Comparative Analysis for Some Sample Different Cancer Diseases Systems.

Ref.	Body's Sections	Segmentation	Feature Extraction (FE.)	Methods of Classification	Accuracy	Year
[4]	Brain	expectation maximization clustering algorithm (EM)	Gray Level Co-occurrence Matrix (GLCM)	Feed forward backpropagation NN classifier	The suggested system is a sufficient system for detecting tumor and classifying given MRI images in the timorous and normal images	2016
[5]	Brain	adaptive pillar K-means algorithm ROI	Gray co matrix calculates GLC matrix shape and texture features	Self-organizing map SOM NN, SVMs	The SVM effectively classified images with a high accuracy and it also assured maximal accuracy of 89.50%.	2017
[8]	breast		(DSIFT)	Discrete Curvelet Transform (DCT) and Multi-Layer Perceptron (MLP)	Results of the numerical validation and graph show the importance of the suggested approach in comparison with the existing state of art methods.	2017
[6]	Brain	Patch based K-means for skull stripping Rough-fuzzy C-means (RFCM) for the identification of the tumor region	Measurement of shape-based features for exacting the area of the tumor		RFCM approach achieved the most promising results with a higher accuracy compared to the FCM (fuzzy C-means) and HCM (hard C-means).	2018
[9]	Breast		texture features GLCM features rank feature method	Artificial Neural Network (ANN) classifier	The general accuracy that has been accomplished with the use of the approach has been 99.40%	2018
[11]	bone	Edge detection superpixel segmentation and multilevel segmentation	GLCM	ANN	The proposed method will drastically reduce the time that is needed for detection and classification of cancer.	2018

					The proposed system successfully detected bone cancer from the images of the CT scan. This system achieved its desired expectations.	
[12]	bone	K-Means clustering algorithm and Fuzzy C-Means algorithm And Super-Pixel Segmentation	machine learning algorithm	supervised learning the RF and nearest neighbor algorithm	This study has been dedicated specifically for detecting bone tumor. In addition to that, it has been carried out in the openCV for the purpose of increasing the speed of the system, as well as its convenience.	2018
[13]	bone	binarized image and connected component labelling algorithm	GLCM)	ANN	The obtained performance of the results of the classification have exhibited that the NN provided 92.5% success in the classification of the bone tumor.	2018
[14]	liver	marker controlled watershed segmentation & Gauss mixture model (GMM) algorithm	texture features	deep neural network (DNN)	A classification accuracy of 99.38% has been achieved, and a Jaccard index of 98.18%, at 200 epochs	2018
[16]	kidney	-------------	Neighbourhood Component Analysis (NCA)	Long Short Term Memory (LSTM)	the LSTM algorithm has been capable of grouping the kidney cancer miRNAs to 5 sub-types with an average accuracy of about 95%	2018
[7]	Brain		(LTPs) and (LQPs).	SVM and KNNs classifier	The algorithm gives the accuracy of 97.5%	2019
[10]	Breast	Thresholding method and Region based segmentation method	DCNNs	SVMs	the accuracy of the SVM becomes 87.20% with an AUC of 0.94 (i.e. 94%). This has been the highest AUC value in comparison with the previous work that used the same conditions	2019
[17]	Lung	K-means algorithm and edge sharpening filters		Convolutional Deep Neural	CDNNs have presented better performances	2019

				Networks (CDNN)	compared to the conventional DNNs. They have obtained the best 0.9962 accuracy, while regular CDNN could only obtain a 0.876 accuracy	
[15]	Liver &brain	DWT	CNN	long short-term memory (LSTM)	With the use of CNN–DWT–LSTM hybrid approach, a 99.10% accuracy has been accomplished in liver tumor classification and a 98.60% accuracy rate has been accomplished in the classification of the brain tumor.	2019
[18]	Lung	Otsu's thresholding method and CNN	PCA	Logist Boost, Bagged and SVM	The suggested system could provide a 99.23% accuracy With the use if the logic boost classifier	2019

4. Conclusion

In this research a comprehensive survey of different image processing techniques for medical image that was specifically examined for cancer diseases in most parts of the body. These sections are: the bones, the liver, the kidneys, the breast, the lung, and the brain. Medical imaging discovery includes various stages like segmentation, image preprocessing, classification and feature extraction. The segmentation techniques include different methods like thresholding, EM, fuzzy c-means, k-means algorithm, edge detection superpixel, binaried image, connected component labeling algorithm, marker controlled watershed segmentation & Gaussian mixture model (GMM) algorithm and region detection. The feature extraction are used include different methods like GLCM, matrix shape and texture feature, DWT, Measurement of shape based features, KTPs and LQPs, DSIFT, DCNN, machine learning algorithm, convolutional neural network, NCA and principal component analysis (PCA). The classification techniques include different methods like propagation neural network, SOM, SVM, DCT and MLP, ANN classifier, long short-term memory (LSTM) and CDNN.

Compliance with ethical standards

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Disclosure of conflict of interest

All authors declare that they have no conflict of interest.

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