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HIGHLY ACCURATE PENTA CANCER DETECTION

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Abstract - *In this paper, we first describe the basics of the field of cancer diagnosis, which includes steps of cancer diagnosis followed by the typical classification methods used by doctors, providing a historical idea of cancer classification techniques to the readers. These methods include Asymmetry, Border, Color and Diameter (ABCD) method, seven-point detection method, Menzies method, and pattern analysis. They are used regularly by doctors for cancer diagnosis, although they are not considered very efficient for obtaining better performance. Moreover, considering all types of audience, the basic evaluation criteria are also discussed. The criteria include the receiver operating characteristic curve (ROC curve), Area under the ROC curve (AUC), F1 score, accuracy, specificity, sensitivity, precision, dice-coefficient, average accuracy, and Jaccard index. Previously used methods are considered inefficient, asking for better and smarter methods for cancer diagnosis. Artificial intelligence and cancer diagnosis are gaining attention as a way to define better diagnostic tools. In particular, deep neural networks can be successfully used for intelligent image analysis. The basic framework of how this machine learning works on medical imaging is provided in this study, i.e., pre-processing, image segmentation and post-processing. The second part of this manuscript describes the different deep learning techniques, such as convolutional neural networks (CNNs), generative adversarial models (GANs), deep autoencoders (DANs), restricted Boltzmann's machine (RBM), stacked autoencoders (SAE), convolutional autoencoders (CAE), recurrent neural networks (RNNs), long short-term memory (LTSM), multi-scale convolutional neural network (M-CNN), multi-instance learning convolutional neural network (MIL-CNN). For each technique, we provide Python codes, to allow interested readers to experiment with the cited algorithms on their own diagnostic problems. The third part of this manuscript compiles the successfully applied deep learning models for different types of cancers. Considering the length of the manuscript, we restrict ourselves to the discussion of breast cancer, lung cancer, brain cancer, and skin cancer. The purpose of this bibliographic review is to provide researchers opting to work in implementing deep learning and artificial neural networks for cancer diagnosis a knowledge from scratch of the state-of-the-art achievements.*

1. INTRODUCTION

Cancer is the leading cause of deaths worldwide. Both researchers and doctors are facing the challenges of fighting cancer. According to the American cancer society, 96,480 deaths are expected due to skin cancer [11], 142,670 from lung cancer, 42,260 from breast cancer, 31,620 from prostate cancer, and 17,760 deaths from brain cancer in 2019 (American Cancer Society, new cancer release report 2019) [3]. Early detection of cancer is the top priority for saving the lives of many. Typically, visual examination and manual techniques are used for these types of a cancer diagnosis. This manual interpretation of medical images demands high time consumption and is highly prone to mistakes.

For this reason, in the early 1980s, computer-aided diagnosis (CAD) systems were brought to assist doctors to improve the efficiency of medical image interpretation. Feature extraction is the key step to adopt machine learning. Different methods of feature extraction for different types of cancer have been investigated in. However, these methods based on feature extraction have weaknesses. To overcome these weaknesses and to enhance the performance, representation learning has been proposed in. Deep learning has the advantage of generating directly from raw images the high-level feature representation. In addition to deep learning, Graphics Processing Units (GPU) are also being used in parallel, for feature extraction and image recognition. For example, convolutional neural networks have been able to detect cancer with promising performance.
To test these algorithms, there are publicly available datasets. These include INbreast and BreakHis for breast cancer testing; Digital Database for Screening Mammography (DDSM)for mass detection; MITOSTAPIA for mitosis detection; Japenese Society of Radiological Technology (JSRT), The Lung Image Database Consortium (LIDC) and Image Database Resource Initiative (IDRI), and Danish Lung Cancer Screening Trial (DLCST) for lung nodule classification; multimodal Brain Tumor Segmentation challenge (BraTS) for brain cancer identification; and Dermoscopic Image Segmentation (DermIS) as well as data given to the public by

International Skin Image Collaboration (ISIC) for skin cancers.

2. METHODOLOGY

Steps of Cancer Diagnosis

Pre-Processing

Raw images contain noise in it so the first step in detection procedure is preprocessing, i.e., improving the quality of an image to be used further by the removal of unwanted image information, which is referred to as the image noises. Several inaccuracies may occur in the classification if this issue is not entertained properly. In addition to inaccuracies, the requirement of performing this preprocessing is because of low contrast among skin lesion and surrounding healthy skin, irregular border and the skin artifacts, which are hairs, skin lines, and black frames. Many filters can be applied for removal of Gaussian noise, speckle noise, Poisson noise, and salt and pepper noise, including median filter, mean filter, adaptive median filter, Gaussian filter, and adaptive wiener filter. For example, an image containing hairs in it along with the lesion may cause misclassification.

The image noises are supposed to be removed or adjusted by performing pre-processing tasks such as contrast adjustment, vignetting effect removal, color correction, image smoothing, hair removal, normalization, and localization. The right combination of pre-processing tasks gives more accuracy. Some of the preprocessing techniques are black frame removal techniques, automatic color equalization, hair removal technique, dull Razor, Karhunen–Loe'vetransform , Gaussian filter, pseudo-random filter, non-skin masking, color space transform, and contrast enhancement. The MRI images of brain cancer are at first converted into greyscale and then undergo contrast adjustment using smoothing operation. Skull stripping is also performed on brain MRI images using a brain extraction tool (BET) and the extraction of brain tissues from other parts of skull . Using X-ray machines, the computed tomographic (CT) images obtained for lung cancer diagnosis are preprocessed by first converting them into grayscale images, followed by the normalization procedure and noise reduction. These images are then converted into binary images, after which the unwanted part is removed. Preprocessing in breast cancer particularly consists of delineation of tumors from the background, breast border extraction and pectoral muscle suppression. Mammograms, which are used for breast cancer diagnosis, include many noises, which are the high-intensity rectangular label, low-intensity label, and tape artifacts. Thus, mammogram labeling, orientation, and segmentation are done using preprocessing. For prostate cancer diagnosis, transrectal ultrasound (TRUS) images are obtained, which have inherent noise and low resolution of images. The preprocessing module used for the noise suppression and artifacts consists of: (a)tree-structured nonlinear filtering (TSF); (b) directional wavelet transform (DWT); and (c) tree-structured wavelet transform (TSWT).

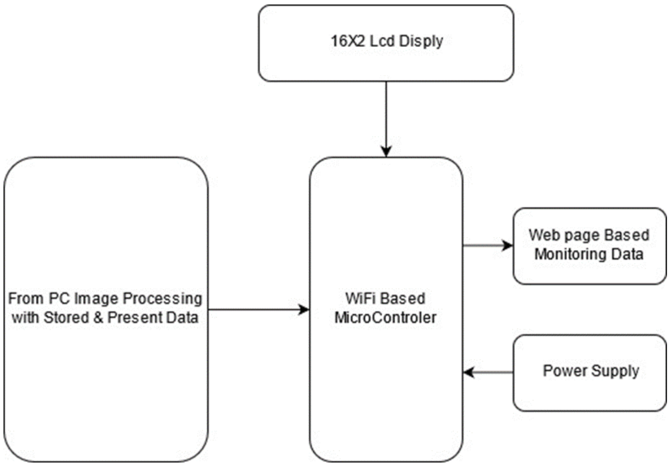
Image Segmentation

Division of the input image into regions where the necessary information for further processing can be extracted is known as segmentation. Segmentation is basically the separation of a region of interest (ROI) from the background of the image. ROI is the part of the image that we want to use. In the case of cancerous images, we need the lesion part to extract the features from the diseased part. Segmentation can be divided into four main classes: (i) threshold-based segmentation; (ii) region-based segmentation; (iii) pixel-based segmentation; and (iv) model-based segmentation. Threshold-based segmentation includesOstu's method, maximum entropy, local and global thresholding, and histogram-based thresholding. Watershed segmentation and seeded region growing are examples of region-based segmentation. Fuzzy c-means clustering, artificial neural networks, and Markov field method are some of the methods of the class of pixel-based segmentation. Model-based segmentation is a parametric deformable model, e.g. level sets. There are many other methods for image segmentation: histogram thresholding, adaptive thresholding, gradient flow vector, distributed and localized region identification, clustering and statistical region growing, bootstrap learning, active contours, supervised learning, edge detection, fuzzy-C Mean clustering, probabilistic modeling, sparse codin, contextual hypergrapp, cooperative neural network segmentation, principle component transform, and region fused band and narrow band graph partition, among others. Hybrid models of these methods by combining two or more have been used to improve the accuracy of the system.

Post-Processing

After passing through the stages of preprocessing and image segmentation, there awaits post-processing where the task is to grab features. To accomplish this, the most common post-processing methods are opening and closing operations, island removal, region merging, border expansion, and smoothing. Some techniques used for the feature extraction are: principle component analysis (PCA), wavelet Packet Transform (WPT), grey level co-occurrence matrix (GLCM) ,fourier power spectrum (FPS) , Gaussian derivative kernels, and decision boundary features. The basic steps of cancer diagnosis are summarized in Table 1.

3. BLOCK DIAGRAM



4. RESULTS AND DISCUSSION

According to the reviewed studies, CNN has the best in performance of all architectures. The winner of ImageNet Large Scale Visual Recognition Competition (ILSVRC) 1998 was LeNet, which is a seven-level CNN architecture, and 2012 it was AlexNet, which is also a very successful version of CNN. From 2012 to 2015, the winner of this competition has been the CNN architectures AlexNet, ZFNet, GoogleNet/ Inception V1, VGGNet and ResNet, which shows the success rate of the CNN architectures in this field. Since these are all different architectures of the same CNN, as the model changes, the only evaluation measure is their percentage performance. As described in the competition, the necessary part was the reduction of top-5 errors, which AlexNet reduced from 26% to 15.3%, while ZFNet reduced to 14.8%. This performance was beaten by the GoogleNet/Inception V4, achieving the error reduction to 3.6%. The best performance was shown by ResNet, which beats the human-level performance by reducing errors to 3.57%.
When implementing deep learning for cancer diagnosis, one of the major challenges becomes a lack of availability of datasets [4]. Every learning algorithm requires a large amount of training for performance measure. However, efforts have been made to make medical images archives containing confidential information of many patients by picture archiving and communication society (PACS). Researchers also use data images from cancer research organizations and hospitals for executing their algorithms. One of the major breakthroughs for data collection was made by Estevaet al. . They collectively made an effort and formed a dataset with 127,463 training images and 1942 test images. Many researchers use a small dataset for their algorithms. In addition, most of the datasets available online with open access have raw images and so researchers are required to obtain the ground truth themselves.
To deal with the issue of limited dataset, a scheme of data augmentation was proposed. Many researchers use data augmentation, which includes techniques such as rotation, cropping and filtering to increase the number of available data [3]. Another way to avoid over-fitting is transfer learning, which has been used by many of the researchers discussed above in this review.
Low contrast and SNR of medical images are responsible for the poor performance of deep learning algorithms. Thus, another issue is how to improve the performance of the proposed model if the data have low contrast and poor SNR. Furthermore, studies based on brain tumor segmentation [12] raised a question: How can we maintain the performance of algorithms on multiple resource data When the algorithms were made to train on multi-institutional data, their performance decreases gradually.

5. CONCLUSIONS

This review focuses on providing all the necessary information to the beginners of this field, starting from the main concepts of cancer diagnosis, evaluation criterion and medical methods. As this manuscript mainly focuses on the deep learning for cancer diagnosis, the most important things to introduce to our readers are all the possible techniques of deep learning that can be used for diagnostic purposes in this document. Furthermore, to facilitate the audience, the respective practice codes for each technique, which are easily available online, are put together in a table. One of the major issues that one can encounter in implementing any algorithm is the dataset availability, therefore all possible access links to the datasets are presented in this work.
Different architectures of CNN are also described in this manuscript. The implementation of the deep learning algorithms for brain cancer, lung cancer, breast cancer, and skin cancer is the focus of this manuscript. The performance measures for different studies are provided. In this review, different deep learning algorithms for classifying different types of cancers are presented. In this review, fifteen studies used Histopath model with CNN for classification and detection of different types of cancers as provided in Table 9. Six of these studies provided the source of data while nine studies did not publish the source of data . Two research studies used mammographs for detection along with CNN [7] and published data source. Eight studies used CT Slices, three of which used data from PROMISE ,and LIDC. Five studies used volumetric computed tomography . Seven studies were for brain cancer classification.

In the field of dermatology, Esteva et al. used pre-trained CNN for skin lesion classification with accuracy of 93.62% .Sabbaghi et al. mapped images to bag-of-feature to increase classification accuracy [1]. Globule patterns on

the skin were detected by Demyanov et al. using a stochastic gradient descent model Yu et al. formed FRCN by replacing the FCN's Conv. layer with the residual layer. Melanoma detection was performed by Nasr et al. by feeding preprocessed images to CNN network model .
Two of the methods reviewed in this study used the ABCDE method for skin cancer detection[11]; they made use of image segmentation, histogram analysis and contour tracing [9] used a graphical user interface to classify skin lesion . whereas fuzzy C Mean was used by Palak et al. for skin cancer analysis. Sumithra et al. used support vector machine for skin lesion classification .

In total, 27 different algorithms provided by 27 different researchers are reviewed for skin cancer diagnosis. As discussed above, there are different methods with different algorithm schemes and different training datasets, which adds difficulty when comparing them. No particular standard can be defined to compare their results.

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