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Cancer Cell Detection Using ANN and Deep Learning Method: A Survey

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Abstract

Improvement in data and technology made an ultra-effect on medical science and which makes the researchers to come up with new methods to improve the classification rate of various diseases. Cancer is a dreadful disease which kills lots of people in the world and also diagnosing this disease in early stage makes a vast impact on its treatment. We survey the usage of deep learning methods and ANN to detect cancer because Deep learning is used for pattern recognition and classification. We end the advantages of ANN, efficiency of deep learning methods for classification of cancer and directions to the future research.

Key Words :*Artificial neural network (ANN), Deep Learning, Cancer.*

INTRODUCTION

Machine-learning provide many features to modern society like recommend the e-commerce websites, web searches to content filtering, and also in consumer products like smartphones and cameras. The deep learning(DL) is the class of technique and this system is used to tape the speech into text, from the images the objects will identified. DL is the machine-learning techniques it has the ability to process the informative data from the raw data and also have ability to convert the raw data into useful data. Many years, developing a machine-learning system needs expertise to design a feature extractor that transform the raw data into an internal representation that could detect or classify patterns from the input. DL contains multiple levels obtained by framing the raw data that transforms the outline of data at one level into abstract level. For discrimination and control the irrelevant variations of the classifications, higher layers of data develop aspects of the input that are important.

Deep learning is mainly used for solving the problems, avoided the best try of the AI community for many years, and applied to many domains of science, and business. This method is beating records in image, speech recognition [1][2] and other ML techniques are used to reconstructing brain circuits[3], predicting the cancer at early stage and also from the gene expression the consequence of transformation in non-coding DNA are predicted4. Deep learning will face more successes soon. ANN known as neural network its structure and function are based on biological NN. It consists of a group of processes information, neurons which is interconnected and has been developed for a wide variety of computational problems in pattern

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recognition, and decision making. ANN is having the ability to change the system structure based on data and during the learning phase the data flows through the network

LITERATURE SURVEY

DL for Identifying Metastatic Breast Cancer

For the detection of breast cancer the ISBI held a grand challenge, the Dayong Wang team won the competition obtaining the AUC of 0.925 and score of 0.7051 for whole slide image classification and tumor localization using whole slide images of biopsies and combining these rate with pathologist's which increases the AUC of 0.995 and reduction of 85% human error rate. These results exhibit the usage of DL to increase improvements in the accuracy of pathologist department. Presented a deep based system for the identification of cancer from WSI of biopsies. This proposed system used deep CNN to make patch-level predictions, separate tumor from normal-patches by using the millions of training patches and collecting the patch-level predictions and perform post-processing over tumor probability heatmaps to predict the slide-based classification task and the tumor-localization task [4]. The dataset provided by Camelyon16 consists of 400 WSI divided into 270 for training and 130 for testing from two institutions Radbound and Utrecht UMC. This team first identify the tissue from WSI and exclude the background white space using the Otsu algorithm [5], which results the average 82% of background region. This detection framework consists of two stages; the 1st is the patch-based classification stage take input as WSI and locating the regions of cancer. From the set of training WSIs the millions of small +ve and -ve patches are extracted. With the help of supervised classification model two classes of patches are discriminated they are positive and negative patches as 0's and 1's. If this patch is located in a tumor regions is a positive patch otherwise, it is a negative patch and these results are combined into a heatmap image. Second stage is to compute the slide and lesion-based evaluation scores for each WSIs using heatmap-based post-processing. And evaluated the performance of four well-known deep network architectures for this classification task: GoogLeNet [6], AlexNet [7], VGG16 [8] and a face orientated deep network [9], from these architectures GoogLeNet and VGG16 resulted as best classification performance. GoogLeNet is faster and stable than VGG16. GoogLeNet are used to generate the tumor-probability heatmaps and noted the errors. These error are due to false positive classification and tend to increase the well performance on these regions by extracting additional training samples from difficult negative regions, each pixel of heatmaps contains a value between 0 and 1 indicating the pixel tumor and performs post-processing to obtain slide-based and lesion-based scores for each heatmap. This system won the Camelyon Grand Challenge of 2016 and finally, combining this predicted system with a pathologist's results produced a reduction in the error rate.

DL for Magnification Independent from Breast Cancer

The author proposed this system by using convolutional neural networks (CNNs) to classify the cancer from histopathology images and also proposed two different Architectures called single task and multi-task CNN which is used for predicting both malignancy and image magnification level concomitantly. The author used BreaKHis database contains 7,990 histopathology images of 82 patients. From the 7,909 images separated 2,481 benign and 5,428 malignant images. [10] CNN shows the improvements in state-of-the-art recognition and classification approaches and it helps to solve various problems in medical research. For example, Ciresan et.al [10] detects mitosis from breast cancer histology images and has been also used in cell classification [11], tumor cell detection in blood samples [12]. Magnification models are scalable, by introducing new samples from any level will be make used and train the models easily and also be easily tuned. Multi-task prediction does not

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require additional computation like single-task prediction. Evaluations and results are carried on dataset. Unlike other methods, this system has direct benefits from additional training data, and from same or different levels it will be captured.

Deep CNN for classifying head and neck cancer

In this paper deep CNN is used to classify the normal and cancerous tissues of head and neck. For this study, three tissue samples are collected from each patient totally 88 tissue samples are collected from 50 head and neck cancer patients with the help of Emory University Hospital pathology team, in order to obtain the hypercube, the samples are imaged with HSI. From out of 52 patients, 28 had squamous-cell carcinoma and 22 had thyroid carcinoma. To classify the cancerous patches from normal patches the CNN was implemented and TensorFlow is used. The architecture consists of 7 convolutional layers and 3 fully connected layers. From five epochs of data the CNN trained for 26,000 steps using a batch size of 250. From the database the patient sample data had 96% accuracy. Experimental results show CNN has capacity in labelling of cancer and classify the normal tissue using hyper spectral images to detect the cancer. The technique used in this study is reliable and does not require postprocess to obtain the results.

Colon Detection Using Deep CNN and Post Learning

Author approached region-based CNN for the automatic detection of polyps from the images and videos of colonoscopy and used deep-CNN model in detection system. This study focused on the polyp detection task using the DL approach and the main obstacle is the unavailable of datasets. For the automatic polyp detection, the Faster R-CNN framework is applied. Due To limited samples this system adopted a transfer learning system using a deep CNN model. For this study the datasets, CVC-CLINIC [10] and ETIS-LARIB [11] are used, the dataset subsumes 195 polyp images which are generated from 35 colonoscopy data. This dataset contains 44 different polyps, 612 images from the two datasets are used for detection. A Faster R-CNN method the main advantages of this proposed system is the detection performance in terms of precision, RT of image and video datasets. The proposed system is trained using WSI instead of CNN patches; the detection process time in each dataset is about 0.40 sec. and this is the disadvantages of this study.

Lung cancer diagnosis using DL algorithms

Author propped the usage of deep algorithms for lung cancer diagnosis from the samples of LIDC database. The radiologists provided the marks accordingly and the nodules of each CT slice were segmented. This system acquired 174412 samples after down sampling and rotating 52 by 52 pixels. Totally 3 types of dl algorithms are used in this paper are CNN, DBN, SDAE and compared these 3 algorithms with the performance old system called computer aided diagnosis (CADx). The accuracies of CNN, DBNs, and SDAE are 79, 0.81, and 79, and CADx is 0.79 and lower than CNN and DBNs and 4% larger than the unlabelled nodules using DBNs this may be results from using the down sampling process and also due to lost some information of nodules. Compared these performances of 3 algorithms attain the highest accuracy of 0.81 by using DBNs. This accuracy rate is higher than traditional system. The comparison results are demonstrated in this to show the potential of deep learning algorithm.

Locality Sensitive Deep Learning for Detecting Colon Cancer

In this study, the author proposed a method called SC-CNN to detect nuclei and this method lapse the probability of pixel and proposed a system novel NEP combined with CNN for classify the nuclei, helps to predict the label of the class of detected cell nuclei accurately. This system does not require segmentation for detection and classification of nuclei. The large datasets consist of more than 20,000 defined nuclei are extracted from colorectal

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adenocarcinoma images; these nuclei are belonging to four different classes. Result of this model shows NEP provides the highest average F1 that compared to SC-CNN and, that potentially leads to a better understand of cancer and also this proposed method used in this paper offers benefits to pathology team in term of analysing the quantitative tissue constituents from the whole-slide images.

CONCLUSION:

Cancer is a fatal disease which causes lots of death all around the world detecting the cancer at early stage is a challenging one but if it is detected at early stage it is curable. But even though complete cure of this disease is still not discovered. Cancer prediction system estimates the risk of the different cancers from examining the many numbers genetic and external factors. This system is validated by comparing its predicted results with the patient's med records and Deep Learning in the early detection of cancer can save countless lives. So, the proposed system uses ANN algorithm to train the deep learning method. In the future, proposed model is to improve the rate of accuracy. All the metadata attributes and fields of parameter are trained into the single layer algorithm using ANN and Deep learning method.

TECHNIQUES	AUTHOR	YEAR	CANCER TYPE	DATASET
• **Patch based classification** • **Slide based classification** • **Lesion based classification**	Dayong Wang	2016	Breast Cancer	Camelyon16 Dataset
CNN	Neslihan	2016	Breast Cancer	Break His dataset
Deep CNN	Halicek M	2017	Head and Neck Cancer	Dataset from Emory University Hospital Midtown surgical and pathology team
region-based CNN	Younghak Shin	2018	Colorectal cancer	CVC-CLINIC and ETIS-LARIB datasets
1. CNN **2. DBN** **3. SDAE**	Wenqing Sun	2016	Lung cancer	LIDC database
SC-CNN	KorsukSirinukunwattana	2016	Colon Cancer	images of colorectal adenocarcinomas

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