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Research Progression of Colposcopy Image-assisted Diagnosis Based on Deep Learning

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Abstract

Cervical cancer is one of the most common malignant tumors in women; hence the world has been working to improve the effective screening and prevention of cervical cancer. Colposcopy plays a central role in cervical cancer prevention, but its accuracy and reproducibility are still limited. The use of deep learning in the field of medical images allows more researchers as well as to explore the application of deep learning in colposcopy image-assisted diagnosis. In this paper, we summarize the research status of this field and propose the current shortcomings and improvement directions this research field.

Keywords: Deep learning; Medical image; Colposcopy; Cervical cancer

1. Introduction

Cervical cancer is a common reproductive system malignancy in women and has become a major public health problem[1]. In 2020, there will be about 600,000 new cases of cervical cancer worldwide, accounting for 5% of all new cancer cases. Of these cases, there are about 120,000 new cases of cervical cancer in China, resulting in about 60,000 deaths[2]. Cervical cancer seriously threatens women's health and increases the burden on individuals, families, and societies. With the continuous improvement of cervical cancer screening technology in recent years, more advanced technologies and equipment are gradually being used in clinical prevention and early diagnosis of cervical cancer. As routine auxiliary examination equipment, a colposcopy can observe subtle lesions that cannot be seen with the naked eye and can improve the accuracy of the diagnosis by combining human papillomavirus detection, cytology examination, and biopsy pathological examination, etc—providing strong technical support for early prevention and treatment of cancer.

With the application of colposcopy, the work tasks of gynecological colposcopy experts have significantly increased, and long-term mechanical observation by the naked eye can easily tire the investigator, thus affecting the subjective judgment of gynecological colposcopy experts and improving the human diagnosis error in the diagnosis results of colposcopy. In addition, the unbalanced development of the world economy, medical conditions, and the professional and technical level of medical personnel are not conducive to promoting colposcopy in grass-roots areas lacking experienced doctors. With the continuous development of computer technology, deep learning has been gradually applied to various clinical diagnosis and treatment stages. Implanting deep learning technology into existing colposcopy equipment and deep learning technology assisting colposcopy equipment to interpret the results of the acetowhite experiment automatically is an effective way to solve this problem.

2. Advance in medical image classification and recognition based on deep learning

Deep learning is a kind of data-based learning and also a kind of machine learning. Its ultimate goal is to make machines able to analyze and learn data such as words, images, and sounds like humans[3]. Its history originated in the 1940s, but it didn't start to rise in the name of deep learning until 2006[4]. Many automatic or semi-automatic image analysis algorithms have been used in cancer detection and diagnosis. In 2014, Wu K. et al.[5] proposed a deep learning-based contrast-enhanced ultrasound imaging classification method. The method first retrieves dynamic CEUS videos of liver perfusion, then uses sparse non-negative matrix factorization to extract temporal intensity curves from the dynamic CEUS videos, and finally uses deep learning to classify the CEUS images of benign and malignant focal lesions of the liver. Extensive experimental results show that this method is superior to conventional classification methods in terms of accuracy, sensitivity, and specificity. In 2015, Brosch T. et al.[6] studied a convolutional deep belief network (DBN) while considering the depreciation of the number of spatial transformations in the frequency domain, which opened up a new direction in the field of analyzing 3D images using deep learning. In 2016, Kleesiek J. et al.[7] proposed a 3D convolutional deep learning architecture for deep brain magnetic resonance image extraction that can handle any number of modalities, which can be used in large-scale research and clinical trials. In 2017, Liu Changzheng[8] et al. conducted autonomous learning and classification of CT image features of many different pneumonia types based on an improved convolutional neural network (CNN), with an accuracy rate of 87.1%. In 2017, the study by Aubreville M. et al.[9] showed that the average accuracy of confocal laser endoscopic image recognition of oral squamous cell carcinoma by CNN was 88.3%, and the sensitivity was 86.6%, and the specificity was 90%. As mentioned earlier, the number of applications of artificial neural networks is increasing and is being used more and more in various fields of medicine. With the continuous development of deep learning technology, the diagnostic accuracy of this technology in medical imaging continues to improve, creating higher value for assisting medical image diagnosis.

3. Research progress of deep learning in colposcopy image-assisted diagnosis

Colposcopy was initially developed to detect invasive cancer. Still, since the abandonment of diagnostic cervical conization more than half a century ago, colposcopy and biopsy have become diagnostic tools for women with abnormal cervical findings[10]. Colposcopy is a mature method of examining the cervix under a magnifying glass. The cervix is infiltrated with 3%-5% acetic acid. Colposcopy can detect and identify cervical intraepithelial lesions[11]. Due to the quality of the colposcopy image itself, the shooting environment's complexity, and its non-repeatability, its diagnostic accuracy is limited. With the development of computer technology, more and more scholars have studied the application of deep learning to colposcopy image-assisted diagnosis. In 2010, Zhang S. et al.[12] proposed an optical image segmentation method of the cervix based on reconstructed sparse representation.

Due to the extensive changes in image appearance due to changes in illumination and specular reflection, color and texture features in optical images often overlap and cannot be linearly separated by using the k-singular value decomposition (K-SVD) method to create a sparsely represented positive dictionary and negative dictionary. Finally, the reconstruction errors of the sparse coefficients are calculated and compared for classification purposes. In 2014, Simões PW. et al.[13] proposed a method to classify colposcopy images using artificial neural networks (ANNs) to identify colposcopy patterns, using a hybrid neural network based on Kohonen self-organizing mapping and multi-layer perceptron (MLP) network. A comprehensive, descriptive, and analytical study of quantitative methods focusing on diagnosis. In 2016, Devi M. et al.[14] proposed an artificial neural network (ANN)-based method to classify normal and abnormal cells in the cervical region. The classification of normal, abnormal, and cancer cells of the cervix by artificial neural network are more accurate than manual screening such as Pap smear and liquid cytology-based (LCB) detection. The classification of normal and abnormal cervical cells has a certain reference value. In 2017, Sun G. et al.[15] proposed a random forest classifier (RF) cervical cancer diagnosis framework based on reliable feature selection. A total of 20 features were extracted through preprocessing, segmentation, and feature extraction. In the classification stage, the RF method is used as the classifier, and different feature dimensions are selected to train the classifier. In 2017, Haidar A. et al.[16] proposed an automated localization algorithm based on fusion, which divides epithelial cells into ten segments, uses image processing and machine vision algorithms to extract features from each component, and then uses these features to identify The segment is classified, the fusion results are used to classify the entire epithelial cell, the 10 line segments are divided into three parts, and the three parts are classified using a convolutional neural network. The results were then fused to classify individual segments and the entire epithelium to classify the squamous epithelium of cervical intraepithelial neoplasia (CIN) into normal, CIN1, CIN2, and CIN3 grades. An alternative of this algorithm employs novel acellular and atypical cell concentration features to calculate vertical segment partitioning of epithelial regions to quantify the relative increase in the number of nuclei with increasing CIN level, employs support vector machines (SVM) and linear discriminant analysis (LDA) compared the two methods for the research method of image-based epithelial cell grading[17], the algorithm has an accurate classification accuracy rate of 77.27% on the same dataset, which is better than another research method on the same dataset (The correct rate is 75.75%). In 2018, Sato M. et al.[18] proposed using the Keras neural network and TensorFlow library to apply deep learning to colposcopy image classification, proving that deep learning technology can be used in the clinical practice of colposcopy image-assisted diagnosis. With the development of deep learning, more and more neural networks are applied to colposcopy image processing methods. Deep learning has the potential to become a new technology to replace traditional cervical cancer screening for colposcopy image analysis technology.

4. Application of deep learning in colposcopy image diagnosis

As the performance of deep learning in colposcopy-assisted diagnosis is improving, many studies have proved its significance in detecting early cervical cancer. The following summarizes some of the recent application studies of deep learning in colposcopy image diagnosis. In 2009 Greenspan H. et al.[19] proposed using a multi-stage scheme to segment and labeled anatomical regions of interest for automatic analysis of cervical maps. The research has continuously improved the steps and methods of automatic analysis of cervical images. The final results show that the recognition results of the cervix and cervical os of the automatic algorithm are similar to those of human experts. However, this study did not further segment the acetowhite region. Subsequently, in 2010 Alush A. et al.[20] proposed a method to automatically extract and segment class-specific objects (or regions) by learning class-specific boundaries. This method identifies lesion areas in uterine cervix images through automatic extraction and localization methods. The study was the first large-scale work to extract lesion areas from cervical images at the time automatically. However, the experimental data of this study showed that the identification of cervical lesions and the diagnosis results of human experts are very different, and the sensitivity is only 60%. In 2011, Park SY. et al.[21] proposed a region-specific automatic image analysis framework for detecting cervical precancerous lesions and cervical cancer. The method utilizes features such as acetic acid whitening, punctate, atypical blood vessels, and mosaicism to identify cervical lesions in clinical colposcopy images. Performance in identifying potentially cancerous cervix areas as tested against cervical biopsy results. Data from this study, comparing colposcopy images from 48 patients, showed that the method had an average sensitivity of 70% and a specificity of 80% in detecting tumor areas.Compared with the 60% sensitivity and 70% specificity of colposcopy, it demonstrates the superiority of automated colposcopy image analysis. In 2014, Simões PW. et al.[13] proposed using artificial intelligence neural network to classify colposcopy images, a lateral, descriptive, and analytical study of quantitative methods focusing on the diagnosis. Pattern classification was performed on point images obtained by colposcopy. The study was continuously trained, tested, and validated on 170 images in the database. The best result in 126 rounds of validation had an accuracy rate of 72.15%, a sensitivity of 69.78%, and a specificity of 68%. Although this study's accuracy, sensitivity and specificity are not high, it is highly innovative, and its value demonstrates the great potential of neural networks in colposcopy image-assisted diagnosis. In 2018, Sato M. et al.[18] discussed whether deep learning can be successfully applied to the classification of colposcopy images. Using preoperative colposcopy images as input data, patients were divided into three groups: severe dysplasia, carcinoma in situ, and invasive carcinoma, and the accuracy of the final validation dataset reached about 50%. In clinical practice, clinicians often classify cervical lesions as cervical intraepithelial neoplasia grade I, cervical intraepithelial neoplasia grade II, cervical intraepithelial neoplasia grade III, or low-grade squamous intraepithelial neoplasia with For high-grade squamous intraepithelial lesions, no clinical classification is considered necessary for high-grade dysplasia and carcinoma in situ, as there is little difference in diagnosis and treatment between the two conditions. In addition, colposcopy terminology is not strictly defined, so a realistic and reliable classification model cannot be constructed based on colposcopy terminology, and the diagnosis of colposcopy is influenced by human perception. In deep learning, the accurate classification result of the output image is very important. Although the accuracy rate of the final validation dataset of this study is not high, the purpose of this study is not to emphasize the accuracy rate itself but to demonstrate that deep learning can be applied to assist colposcopy diagnosis in clinical practice. In 2020, Miyagi Y. et al.[22] studied the feasibility of classifying cervical squamous epithelial lesions from colposcopy images combined with human papillomavirus (HPV) types using deep learning. Using cervical biopsy results as the gold standard, the study data showed that the accuracy, sensitivity, specificity, positive predictive value, and negative predictive value of the artificial intelligence classifier and gynecological oncologist were 0.941 and 0.843, 0.956, respectively, and 0.844, 0.833 and 0.833, 0.977 and 0.974, 0.714 and 0.500. The study data results suggest that the AI classifier outperformed gynecological oncologists, although not significantly. Although further research is needed, it may be feasible to apply artificial intelligence to classify cervical intraepithelial lesions by colposcopy and HPV type in the clinic.

To sum up, the automatic extraction and segmentation of cervical lesions by colposcopy using deep learning technology is becoming more and more accurate, the classification of cervical lesions is becoming more and more refined, and the accuracy of cervical cancer diagnosis is getting higher and higher. However, these studies also show that this new technology still needs continuous improvement to be effectively used in clinical practice.

5. Conclusion

The application of deep learning technology in colposcopy image-assisted diagnosis has become increasingly mature and continues to create new heights. Judging from the current research background of deep learning, the recent research in this field still has the following shortcomings. First, most research objects are patients who have been confirmed to have cervical squamous intraepithelial lesions. Patients with low-grade cervical squamous intraepithelial lesions or even no lesions also have a certain degree of acetowhite reaction after the acetic acid test. Screening for cervical cancer is equally important. Secondly, the segmentation accuracy of the acetowhite region is relatively low, and there are many false positive or false negative regions in the segmentation results. With the advancement of hardware functions and the improvement of algorithm structure, deep learning technology will develop in the direction of higher accuracy, higher adaptability, and broader scope of application in the field of colposcopy image-assisted diagnosis, providing a comprehensive reference for clinical diagnosis and treatment.

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