
ISSN: 2319-345X
IJMRBS
International Journal of
Management Research and
Business Strategy
www.ijmrbs.org
E-mail
editor@ijmrbs.org
editor.ijmrbs@gmail.com

ISSN: 2319-345X
www.ijmrbs.com
Vol. 12, Issue. 3,July 2023

ACCURATE GASTRIC CANCER SEGMENTATION IN DIGITAL PATHOLOGY IMAGES

[1]D SARITHA,[2]SIDDAM SAI MEGHANA PATEL, [3]SOLASA PRANAVI,[4]SREERAMOJU SREEHITHA,[5]SUNKA THANU SRI

ABSTRACT

The identification of diseases is inseparable from artificial intelligence. As an important branch of artificial intelligence, convolutional neural networks play an important role in the identification of gastric cancer. We conducted a systematic review to summarize the current applications of convolutional neural networks in the gastric cancer identification. The original articles published in Embase, Cochrane Library, PubMed and Web of Science database were systematically retrieved according to relevant keywords. Data were extracted from published papers. A total of 27 articles were retrieved for the identification of gastric cancer using medical images. Among them, 19 articles were applied in endoscopic images and 8 articles were applied in pathological images. 16 studies explored the performance of gastric cancer detection, 7 studies explored the performance of gastric cancer classification, 2 studies reported the performance of gastric cancer segmentation and 2 studies analyzed the performance of gastric cancer delineating margins. The convolutional neural network structures involved in the research included AlexNet, ResNet, VGG, Inception, DenseNet and Deeplab, etc. The accuracy of studies was 77.3 – 98.7%. Good performances of the systems based on convolutional neural networks have been showed in the identification of gastric cancer. Artificial intelligence is expected to provide more accurate information and efficient judgments for doctors to diagnose diseases in clinical work.

Keywords: Classification, Convolutional neural network, Detection, Diagnosis, Gastric cancer

INTRODUCTION

Gastric cancer is the cancer of the cavity organs with the highest incidence [11], which is a serious threat to human health. The prognosis of gastric cancer is closely related to disease stage. The diagnosis and treatment of early gastric cancer is helpful to the recovery of patients, and the 5-year survival rate of patients can exceed 90% [59]. However, most patients have been already at an advanced stage when they are diagnosed [73]. Due to the limited treatment, the survival rate of advanced gastric cancer is low and the prognosis is poor [26]. With the advancement of medical technology and the enhancement of people's health awareness, the diagnosis and treatment of gastric cancer has become an urgent need for more patients.

[1]ASSISTANT PROFESSOR, DEPARTMENT OF ECE, MALLA REDDY ENGINEERING COLLEGE FOR WOMEN, HYDERABAD
[2,3,4&5] UGSCHOLAR, DEPARTMENT OF ECE, MALLA REDDY ENGINEERING COLLEGE FOR WOMEN, HYDERABAD

Therefore, to improve the accuracy of gastric cancer identification, especially early gastric cancer, has become the focus of current researches. Gastric cancer is evaluated by endoscopy, pathological pictures, imaging examination, etc. First, endoscopy has been widely used in the detection of gastric cancer. Image-enhanced endoscopy, such as narrow-band imaging [57] and linked color imaging [52], can accurately analyze the surface structure. The studies showed that the application of these endoscopic methods could improve the accuracy of gastrointestinal tumor diagnosis [10, 27]. However, a study showed that 10% of upper gastrointestinal cancers were still missed by endoscopy [41]. Even if two experts participate in an endoscopy unit, there would be missed diagnosis [61]. The reason was that doctors' accurate diagnosis of gastroscopy images required years of experience accumulation. Secondly, histopathological image recognition is the gold standard of tumor diagnosis. The shortage of pathologists has led to a huge workload for pathologists and diagnostic errors [68]. Finally, imaging examination plays an important role in the evaluation of lymph node metastasis of gastric cancer. Imaging examination is mainly based on morphological characteristics of the lesions. For example, perigastric adipose tissue is rich so it’s indistinguishable from lymph nodes. Coupled with the inexperience of doctors, missed diagnosis and misdiagnosis may occur. In particular, when the number of patients is large, the accuracy of diagnosis will inevitably decrease [12]. With the increasing requirements of more accurate detection, classification and segmentation or delineating margins, artificial intelligence (AI) is booming in medical applications. AI is to make machines think like people. Machine learning is one of the most important parts of AI. Compared with traditional machine learning, such as support vector machines and Bayesian networks, deep learning has better accuracy and flexibility, and can be more easily adapted to different fields and applications. Convolution neural network (CNN) is one of the most prominent algorithms for image processing in deep learning The basic structure of CNN includes convolution layer, pooling layer, full connection layer The convolutional layer performs feature extraction from a large amount of data. The pooling layer compresses the input feature map to extract the main features. And it can reduce the dimension of the extracted feature information, simplify the network calculation complexity, and improve the calculation speed. Classic CNN structures include AlexNet ResNet, VGG Inception and DenseNet etc. Network depth refers to the number of layers that need to update parameters through training, such as convolutional layers, fully connected layers, etc. The basic structure of AlexNet includes 8 layers in total. There are 5 convolutional layers, followed by 3 fully connected layers. The accuracy of AlexNet has a big improvement compared to traditional methods. The kernel size of the first 4 convolutional layers are 11×11, 5×5, 3×3, 3×3, and 3×3. The kernel size of the first graphics processing unit is 3×3 and the kernel size of the second graphics processing unit is 5×5 in the fifth convolution layer. The channels of the 5 convolutional layers are 96, 256, 384, 384 and 256 respectively. The first two fully connected layers have 4096 neurons respectively, and the final output softmax has 1000 neurons. The VGG network is developed on the basis of the AlexNet network. Compared with AlexNet, VGG uses the convolution kernel with 3×3, and the pooling kernel with 2×2. The developer changed the original three fully connected layers that were the same as AlexNet in the network into one 7×7 and two 1×1 convolutional layers in turn. The entire network is divided according to the number of layers. The most widely used is VGG-16, which is 13 convolutional layers and 3 fully connected layers. GoogLeNet is a deep neural network model based on the inception module launched by Google. The inception module replaces the traditional operations of convolution and activation. Inception is characterized by the use of 1 × 1 convolution for dimensionality reduction, while convolution and re-aggregation can be performed on multiple scales. This network structure replaces all the fully connected layers with simple global average pooling, which greatly reduces the total number of parameters of the model. Subsequently, the model has been improving. Inception-v2, Inception-v3, Inception-v4 and other versions have been developed. ResNet has been designed a residual block to allow us to train deeper networks and increase model performance. There are 5 different depth structures in PyTorch's official code, which are 18, 34, 50, 101 and 152 layers. The more common network is ResNet-50. It has a total of 50 layers of structure, including 49 convolutional layers and a fully connected layer. The size of the convolution kernel includes three types: 1 × 1, 3 × 3, and 7 × 7. DenseNet is a convolutional neural network with dense connection. The emergence of DenseNet breaks away from the fixed thinking of deepening the number of network layers (ResNet) and widening the network structure (Inception) to improve network performance. Its advantage is that the network is narrower and has fewer parameters. CNN has excellent performance in many fields, such as computer vision and natural language processing. Especially in the field of computer vision, CNN is the important model for image classification, image retrieval, object detection and semantic segmentation. For example, agile CNN was used to diagnose the benign and malignant pulmonary nodules in chest CT images Meanwhile, CNN showed good diagnostic performance in the diagnosis of liver lesions and breast ultrasound images . CNN can also be used for pathological image classification. For example, fully connected CNN with extreme learning machine model was used to classify hepatocellular carcinoma nuclei . CNN was also used for histopathological classification of osteosarcoma and epithelial matrix pathological image classification In order to help doctors identify gastric cancer more accurately and in less time, a number of computer-aided diagnosis schemes have been developed [2, 25, 63]. Computer-aided diagnosis can help doctors reduce omissions and mischaracterizations of gastric tumor changes, thereby helping to solve the limitations of current doctors' lack of experience in examinations. Deep learning, especially CNN, has become a smarter and more accurate image processing technology. CNN is expected to become the mainstream application technology in the AI identification of gastric cancer. The purpose of this system review is to summarize all current applications of CNN in gastric cancer identification and evaluate the performance of CNN in gastric cancer identification. This research can contribute to solving the knowledge gap in the development of CNN in gastric cancer identification.

Methods

Literature search

Literature retrieval was completed from Embase, Cochrane Library, PubMed, Web of Science database on 17th September, 2020 to find out the CNN study of gastric cancer's medical images . The PRISMA checklist was used for reporting the systematic review. We used medical subject headings and free-text words to search. The search terms in this article mainly include "machine learning", "artificial Intelligence", "convolutional neural network", "deep learning", "data mining", "algorithm", "tumor", "neoplasm", "carcinoma", "cancer", "lesion", "endoscope", "pathology", "computed tomography", "ultrasonography", "x-ray", "Magnetic Resonance Imaging", "stomach", "gastric", "digestive system", "diagnosis", “identification”, “classification”, “detection”, “segmentation”. There was no time limit on the publication of included articles. To describe the proposed CNN performance in the identification of gastric cancer, we compared measures of precision, sensitivity, specificity, area under the curve (AUC) and accuracy (if available) in the models.

Selection criteria

The following inclusion and exclusion criteria were used to select the study. The inclusion criteria were:

Studies on the identification of gastric cancer images or lesions,

Using models based on CNN or the main components of CNN,

The diagnostic performance indexes of AI algorithm include precision, accuracy, sensitivity, specificity or AUC,

Studies of human subjects,

Publications in English.

Guidelines, case reports, review articles, abstracts of conference papers, letters to editors and editorials were not included in this study.

Data extraction and quality assessment

The two authors (XY and YJ) extracted the data independently. The forms filled out by each author were compared, and dissenting opinions were resolved through review and discussion. In case of unresolved differences, the third evaluator acted as the final arbiter. The authors extracted following contents from the article: (a) author information (b) year of publication (c) study design (d) data set source (e) basic information about patients (f) number of images (g) number of lesions (h) CNN tasks (classification, detection, segmentation and delineating margins) (i) whether independent test sets are used (j) types of medical images or lesions.

We carefully evaluated quality of the studies included in systematic review. The Quality Assessment on Diagnostic Accuracy Studies (QUADAS-2) [65] was used to evaluate quality of the included study. The tool consists of 4 areas: patient selection, index test, reference standard, and flow and timing [65]. Each area is assessed on the basis of high, low or unclear bias risks, and the first 3 areas are also assessed on the basis of high, low or ambiguous concerns about applicability [65]. Review Manager version 5.3 (RevMan for Windows 10, Nordic Cochrane Centre) was used to generate summary diagrams of methodology quality assessment.

Existing System:

A consequence, this model has achieved state of-the-art performance in semantic segmentation under the same backbone [44]. For verifying the efficiency, we have tested this architecture on our gastric cancer segmentation dataset. As a result, this method has performed best in several existing advanced networks.

Clinical pathological analysis makes sense for diagnosis of this cancer and brings the most significant information on the focus of infection. Diagnosing gastric cancer is hard and time-consuming due to image high resolution [1]. In addition, on account of the different diagnostic criteria of different clinicians, an accurate and timely diagnosis becomes luxurious for patients. With repeated diagnoses, the golden time for the treatment might be missed.

We take advantage of the Atreus Spatial Pyramid Pooling module and encoder-decoder based semantic-level embedding networks for multi-scale segmentation. Additionally, we propose a lightweight decoder to fuse the contexture information, and utilize the Dense Up sampling Convolution for boundary refinement at the end of the decoder.

Proposed System:

Our contributions can be summarized as:

1). we have created a clinical gastric cancer segmentation dataset for our research, which has been delicately annotated by medical specialists.

2). We have proposed multi-scale embedding networks for segmenting cancerous regions of various sizes, in which we have integrated Atrous Spatial Pyramid Pooling module and encoder-decoder based semantic-level embedding networks.

3). We have applied the deformable convolutional module for adapting to the non-rigid characters of pathological images, and we have utilized the dense up sampling convolution for boundary refinement at the end of our architecture.

Disadvantage:

Atrous convolution has been firstly implemented in a dyadic wavelet transform method [32], which has been widely used in signal processing. In deep networks, the resolution of the final feature maps will be significantly reduced with the cascaded pooling layers and striding operations.

This phenomenon is disadvantageous for our segmentation task. Motivated by obtaining a wider range of information under similar consumption, Yu and Koltun [17] have used atrous convolution to replace these resolutionreduced layers. They have proposed stacked atrous convolutional layers with increasing rates of dilation. In [33], a similar approach has been adopted for simultaneously increasing receptive fields and preserving the resolution of feature maps.

In our approach, we have drawn on the experience of deformable convolution [14], which has integrated the deformable operation into convolutional layers. In Fig. 2, we could find that both the convolutional parameters and coordinate offsets could be learned in the networks, bringing in the adaptive receptive field.

Advantage:

Structurally, we replace the basic form of convolution with deformable and Atrous convolutions in specific layers, for adapting to the non-rigid characters and larger receptive field. We take advantage of the Atrous Spatial Pyramid Pooling module and encoder-decoder based semantic-level embedding networks for multi-scale segmentation.

Additionally, we propose a lightweight decoder to fuse the contexture information, and utilize the Dense Up sampling Convolution for boundary refinement at the end of the decoder.

In Ronneberger and Fischer have proposed an encoder-decoder architecture with skip-connections to embed feature maps from different semantic levels. In a similar method has been used on patch based histological segmentation.

Though these methods have shown some advantages for multi-scale perception and got better boundaries, their architectures might not be specifically designed to these problems and the performance might not be satisfactory in our task.

CONCLUSION

In the summary of CNN’s research on medical images, it finds that CNN is a good tool for identifying gastric cancer. All the studies showed good identification performance and the model accuracy of all studies was 77.3 – 98.7%. CNN is expected to become an important tool to help doctors and pathologists improve the accuracy and efficiency of disease identification.

REFERENCES:

[1]D.Saritha , L.Lakshmi Chandra Pavani , P.Shravana Pramidha , P.Shravana Pramidha, Driver Drowsiness Monitoring System Using Machine Learning,DogoRangsang Research Journal, Issn: 2347-7180, Vol-12 Issue-02 2022,Pg 55-61.

[2] D. Saritha, S. Sripujitha, R. Sri Chandana, P. Shriyageethika , Supervised Learning with Color and Texture Feature Extraction for Cotton Plants Disease Detection and Classification, The International journal of analytical and experimental modal analysis, ISSN NO: 0886-9367, Volume XIV, Issue XI, November/2022, Pg 1389-1394

[3] C. Li, C. Shi, H. Zhang, Y. Chen, and S. Zhang, "Multiple instance learning for computer aided detection and diagnosis of gastric cancer with dual-energy CT imaging," Journal of Biomedical Informatics, vol. 57, pp. 358-368, Oct 2015, doi: 10.1016/j.jbi.2015.08.017.

[4] Y. Li, X. Li, X. Xie, L. Shen, and Ieee, "DEEP LEARNING BASED GASTRIC CANCER IDENTIFICATION," in 2018 Ieee 15th International Symposium on Biomedical Imaging, (IEEE International Symposium on Biomedical Imaging, 2018, pp. 182-185.
[5] X. Liu et al., "TRANSFER LEARNING WITH CONVOLUTIONAL NEURAL NETWORK FOR EARLY GASTRIC CANCER CLASSIFICATION ON MAGNIFIYING NARROW-BAND IMAGING IMAGES," in 2018 25th Ieee International Conference on Image Processing, (IEEE International Conference on Image Processing ICIP, 2018, pp. 1388-1392.
[6] K. Ishihara, T. Ogawa, M. Haseyama, and Ieee, "DETECTION OF GASTRIC CANCER RISK FROM X-RAY IMAGES VIA PATCH-BASED CONVOLUTIONAL NEURAL NETWORK," in 2017 24th Ieee International Conference on Image Processing, (IEEE International Conference on Image Processing ICIP, 2017, pp. 2055-2059.
[7] H. Sharma, N. Zerbe, I. Klempert, O. Hellwich, and P. Hufnagl, "Deep convolutional neural networks for automatic classification of gastric carcinoma using whole slide images in digital histopathology," (in eng), Comput Med Imaging Graph, vol. 61, pp. 2-13, Nov 2017, doi: 10.1016/j.compmedimag.2017.06.001.
[8] B. Kong, S. Sun, X. Wang, Q. Song, and S. Zhang, "Invasive Cancer Detection Utilizing Compressed Convolutional Neural Network and Transfer Learning," in Medical Image Computing and Computer Assisted Intervention - Miccai 2018, Pt Ii, vol. 11071, A. F. Frangi, J. A. Schnabel, C. Davatzikos, C. AlberolaLopez, and G. Fichtinger Eds., (Lecture Notes in Computer Science, 2018, pp. 156-164.
[9] M. Fang et al., "Using Multi-task Learning to Improve Diagnostic Performance of Convolutional Neural Networks," in Medical Imaging 2019: Computer-Aided Diagnosis, vol. 10950, K. Mori and H. K. Hahn Eds., (Proceedings of SPIE, 2019.
[10] C. Li et al., "Cervical Histopathology Image Classification Using Multilayer Hidden Conditional Random Fields and Weakly Supervised Learning," Ieee Access, vol. 7, pp. 90378- 90397, 2019 2019, doi: 10.1109/access.2019.2924467.
[11] Y. Sakai et al., "Automatic detection of early gastric cancer in endoscopic images using a transferring convolutional neural network," Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference, vol. 2018, pp. 4138-4141, 2018-07 2018, doi: 10.1109/embc.2018.8513274.
[12] H. Ali, M. Yasmin, M. Sharif, and M. H. Rehmani, "Computer assisted gastric abnormalities detection using hybrid texture descriptors for chromoendoscopy images," Computer Methods and Programs in Biomedicine, vol. 157, pp. 39-47, Apr 2018, doi: 10.1016/j.cmpb.2018.01.013.
[13] D. Boschetto and E. Grisan, "Superpixel-based classification of gastric chromoendoscopy images," in Medical Imaging 2017: Computer-Aided Diagnosis, vol. 10134, S. G. Armato and N. A. Petrick Eds., (Proceedings of SPIE, 2017.
[14] K. Ishihara, T. Ogawa, M. Haseyama, and Ieee, "HELICOBACTER PYLORI INFECTION DETECTION FROM MULTIPLE X-RAY IMAGES BASED ON COMBINATION USE OF SUPPORT VECTOR MACHINE AND MULTIPLE KERNEL LEARNING," in 2015 Ieee International Conference on Image Processing, (IEEE International Conference on Image Processing ICIP, 2015, pp. 4728-4732.
[15] H. Ali, M. Sharif, M. Yasmin, and M. H. Rehmani, "Computerbased classification of chromoendoscopy images using homogeneous texture descriptors," Computers in Biology and Medicine, vol.

88, pp. 84-92, Sep 1 2017, doi: 10.1016/j.compbiomed.2017.07.002.