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Rapid and accurate intraoperative pathological diagnosis by artificial intelligence with deep learning technology

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ABSTRACT

Frozen section is widely used for intraoperative pathological diagnosis (IOPD), which is essential for intraoperative decision making. However, frozen section suffers from some drawbacks, such as time consuming and high misdiagnosis rate. Recently, artificial intelligence (AI) with deep learning technology has shown bright future in medicine. We hypothesize that AI with deep learning technology could help IOPD, with a computer trained by a dataset of intraoperative lesion images. Evidences supporting our hypothesis included the successful use of AI with deep learning technology in diagnosing skin cancer, and the developed method of deep-learning algorithm. Large size of the training dataset is critical to increase the diagnostic accuracy. The performance of the trained machine could be tested by new images before clinical use. Real-time diagnosis, easy to use and potential high accuracy were the advantages of AI for IOPD. In sum, AI with deep learning technology is a promising method to help rapid and accurate IOPD.

Introduction

Rapid and accurate intraoperative pathological diagnosis (IOPD) is essential for intraoperative decision making [1–3]. Accurate IOPD of the lesions and the margins could guide the extent of resection, which would help improve patients' outcomes, avoid reoperations and lower the costs [2,3]. Besides, accurate IOPD could help decide the intraoperative use of drugs in some cases (for instance, carmustine use during the surgery of high-grade glioma) [1,4]. Nowadays, frozen section is widely used for IOPD [1,5]. Although several studies have suggested high diagnostic accuracy of frozen section [6–8], there is still room for improvement. Moreover, under some circumstances, the misdiagnosis rate of frozen section is high. Basaran et al. found that the agreement between frozen section diagnosis and permanent histology was only 62.7% in borderline ovarian tumors [9], and borderline histology was proven to be an independent predictor (odds ratio: 22.6, $p < 0.0001$) for misdiagnosis during frozen examination in adnexal mass [10]. Also, Ishikawa et al. showed that the temporary WHO grade by frozen section is underestimated in approximately half of glioma cases [1]. Apart from the doubted accuracy, it usually takes 20–30 min for the diagnosis by frozen section [11]. Therefore, new alternative methods with rapid and accurate IOPD would benefit a lot.

The past decades have seen increasingly rapid advances in the field of artificial intelligence (AI), as well as the application of AI in medicine [12–14]. Deep learning is a promising method in AI and could be used in visual object recognition [15]. Recently, two major achievements of AI with deep learning technology implied its bright future in medicine [14,16]. Hazlett et al. [16] used a deep-learning algorithm [15] to predict the diagnosis of autism in individual high-risk children and showed an accuracy of 94%. Esteva et al. also used a deep-learning algorithm to train a computer to develop AI to analyze images and diagnose disease, and demonstrated AI capable of classifying skin cancer with a level of competence comparable to board-certified dermatologists [14]. Based on the inspiring findings, we hypothesize the application of AI with deep learning technology in IOPD.

The hypothesis

We hypothesize that AI with deep learning technology could help IOPD with a computer trained by a dataset of intraoperative lesion images, just like how Esteva et al. did [14]. Esteva et al. used a dataset of 129,450 clinical images to train the computer to recognize skin

Abbreviations: IOPD, intraoperative pathological diagnosis; AI, artificial intelligence

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diseases through a deep-learning approach. Then the diagnostic accuracy level of the trained machine was tested against 21 board-certified dermatologists on previously unseen images of skin lesions. And the machine achieves performance on par with all tested experts. Thus, we hypothesize that we could train a computer to diagnose the intraoperative lesions, using a large dataset of intraoperative lesion images with the corresponding postoperative pathological diagnosis. Then the performance of the trained machine could also be tested by new images. The diagnostic accuracy of the trained machine may be acceptable as long as the training dataset was large enough. At that time, the IOPD would be real-time and the accuracy may be comparable to or even better than that of frozen sections.

Evaluation of the hypothesis

Evidence in support the hypothesis

Intraoperative lesions as well as skin lesions are visible. Esteva et al. have verified the feasibility and accuracy of the trained machine in the use of diagnosing skin cancer [14]. And the deep-learning algorithm is a developed method to train computers [14–16]. Besides, the dataset of the intraoperative lesion images could be very large, and could be updated in real time, thus improving the diagnostic accuracy.

Evidence against the hypothesis

For skin diseases, visual inspection is the primary means by which dermatologists classify them [17]. However, for other tumors, it is hard for differential diagnosis using only intraoperative visual inspection, and we usually need histological evidence or even molecular parameters [18,19]. So our hypothesis of using a trained machine for IOPD with intraoperative lesion images may result in a low diagnostic accuracy. In spite of that, the diagnostic accuracy may be acceptable if the training dataset is large enough.

Test of the hypothesis

To test our hypothesis, a large number of intraoperative lesion images and the corresponding final pathological diagnosis are needed in order to establish a database to train the computer. Esteva et al. used a dataset of 129,450 clinical images of skin lesions [14]. So hundreds of thousands intraoperative images of lesions are needed to establish the database. To start with, it is better to test it among easily visually recognized tissues (like gastrointestinal tumors, rather than intracranial tumors). When should the intraoperative lesion images be obtained is a major question. We suggest obtaining the images before the resection, since the samples may be burned during resection, and will shrink and be deformed after resection. The images should be taken from multi angles. And multicenter images are suggested. Apart from the final pathological diagnosis, the addition of basic characteristics of the patients and preoperative tested markers would also help to improve the power of the algorithm. Besides, information by other techniques may be combined with the photographic images, in order to improve the diagnostic accuracy. For example, Raman spectroscopy could give spectral tissue characteristics based on molecular signatures, and accurately differentiate normal tissues from neoplastic tissues [20–22]. After training the computer, the diagnostic performance could be tested using new images and be compared with intraoperative frozen sections, with the postoperative histological diagnosis as the reference standard.

Implications of the hypothesis

If the hypothesis was confirmed with fine accuracy, it would provide surgeons with real-time IOPD, which would help rapid decision making during surgery and lessen the time of intubation and anesthesia [11]. Secondly, images of the margins could be tested to determine if there is residual tumor. Moreover, the corresponding deep neural networks could be outfitted in smartphones [14], which would make it easy to use and help the surgeons in less developed areas where the intraoperative frozen section is not available. Apart from the intraoperative use, this technique could be applied in the field of endoscopy, such as gastroscopy and enteroscopy, eventually avoiding invasive endoscopic biopsy. However, the major concern about its application is the possible low diagnostic accuracy. As we mentioned above, the size of the training dataset is essential to improve the diagnostic accuracy. Also, basic characteristics of the patients, data of the known markers, and information by other techniques (such as Raman spectroscopy) may be combined with photographic images to improve the diagnostic accuracy. We believe that, with the advance of technology, AI with deep learning technology would help rapid and accurate diagnosis, as well as disease prevention and treatment of in the future.

Conflict of interest statement

All the authors declare no conflict of interest.

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