The Advancements and Applications of Artificial Intelligence in Gastric Cancer Diagnosis

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Abstract: Gastric cancer, a common and deadly malignancy with early detection challenges, benefits from Artificial Intelligence (AI)-enhanced diagnosis, offering faster and cost-effective solutions through advanced imaging and data analysis. This study aims to provide a comprehensive review of the detection of gastric cancer by AI. The research methods mainly include machine learning and deep learning aspects, covering the Convolutional Neural Network (CNN) and random forest and other methods. In terms of traditional machine learning methods, this paper detailed the application of random forest and Support Vector Machine (SVM) in the detection of gastric cancer. Random forest is used to predict patient survival status, improving the generalization ability of the algorithm by weighting methods. The SVM is used to identify Microsatellite Instability (MSI) and Lymph Node Metastasis (LNM) to provide doctors with important information to guide treatment decisions. In terms of deep learning methods, this paper focused on the application of CNNs for gastric cancer detection. The research team developed a model for the detection and depth prediction of Early Gastric Cancer (EGC), which improved the detection accuracy of EGC by segmenting endoscopic images and classifying them using the VGG-16 model. The discussion section discusses in detail the shortcomings of AI models in gastric cancer detection, such as poor interpretability, insufficient data diversity, difficulties with physician and model coordination, and privacy and ethical issues. Relevant suggestions are made, including injecting more domain knowledge, enhancing data diversity, optimizing real-time models, enhancing collaboration between doctors and models, and adopting privacy protection technologies.

1 INTRODUCTION

Gastric cancer is a malignant tumor originating from gastric tissue, which usually develops relatively slowly and may have no obvious symptoms at the initial stage. The harm of gastric cancer is mainly reflected in the following aspects: It is challenging to detect at the early stage, because the initial symptoms of gastric cancer are atypical, and patients may feel slight discomfort or indigestion, which is easy to be ignored. Therefore, many times have progressed to the end of detection. Nowadays, the treatment of gastric cancer is mainly based on hospital diagnosis, which leads to poor real-time performance required to be improved, and high labor costs. Therefore, it is necessary to find a better auxiliary method. Artificial intelligence has the powerful capability to extract high-level representations and predict based on the image analysis, data integration and analysis, and surgical assistance, which can be considered in this case.

Machine learning is a very important application of artificial intelligence, which uses mathematical methods to solve this mathematical model, so as to solve the problems in real life. The mainstream algorithms of it include many methods, such as random forest, Support Vector Machine (SVM). In addition, there are also neural network methods for deep learning. Random forest is a classifier of tree structure, and the most popular tree is selected when there are many trees in the structure (Le Gall, 2005). The SVM is an algorithm used to solve the binary classification problem, where the goal is to find a division so that all the elements of the two classes to this division add up to the maximum (Cortes & Vapnik, 1995). A neural network is a computational model that simulates the working mode of human brain nerves (Domingos, 2012).

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In recent years, many studies have considered the combination of artificial intelligence algorithms and medicine, especially for gastric cancer detection, with specific related work. For instance, Yohei et al constructed a Convolutional Neural Network (CNN) using over 13,000 EGD images and tested it by comparing its ability to diagnose early gastric cancer with that of many endoscopists (Ikenoyama et al, 2021). Hong et al built an optimized Early Gastric Cancer (EGC) detection and depth prediction model and studied the influencing factors of Artificial Intelligence (AI) diagnosis (Yoon et al, 2019). Cheng Xu et al used a weighted improved random forest algorithm to complete the gastric cancer test of the 110,697 patients (Xu et al, 2022). Shuang-Li Zhu et al used Gradient Boosting Decision Tree (GBDT), a type of machine learning method, to construct a predictive model for the diagnosis of gastric cancer and evaluate the accuracy of the model (Zhu et al, 2020). Due to the rapid development of this field and its great importance, it is necessary to make a comprehensive review of this field.

The rest of this article contains three sections, which are methods, discussion and conclusions. In the second part, this paper will investigate some classic machine learning and deep learning algorithms and gastric cancer detection work and introduce their implementation process. In the third part, it discusses the shortcomings of the current algorithm and the future development direction, and in the fourth part, the conclusion summarizes the full text.

2 METHOD

2.1 Framework of Machine Learning Model

Machine learning model in gastric cancer medical prediction, it mainly consists of 6 procedures including collecting data, data preprocessing, feature extraction, model building, model testing and evaluation as well as model deployment as shown in Fig. 1. More details can be found as below.

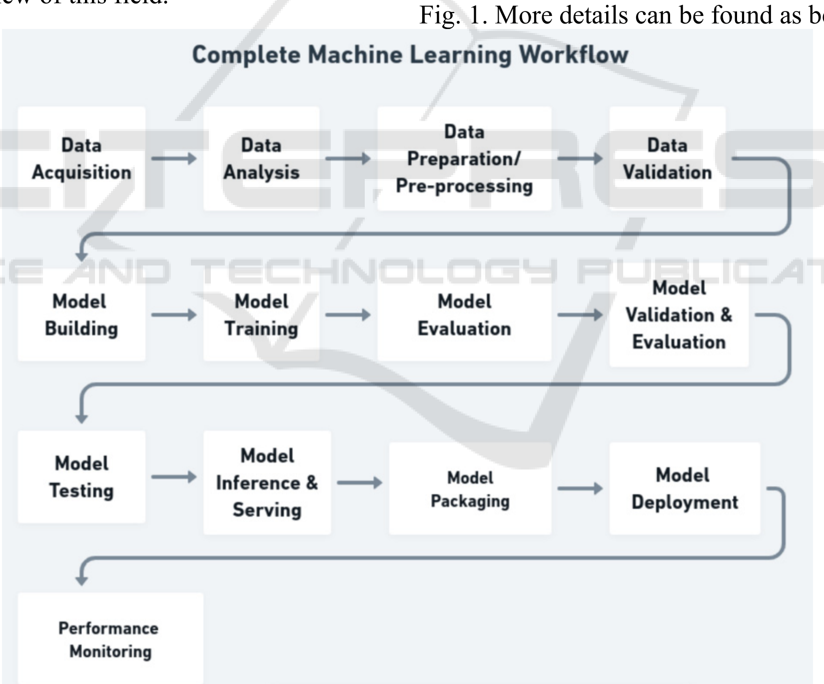

Figure 1: The detailed workflow of developing machine learning models (Morris).

Collecting data: Multiple patient-related data were collected, including clinical medical records, imaging data (e.g. CT, MRI scans), laboratory findings, etc. A large-scale patient data is also required to cover information on different cases, different disease stages and treatment options.

Data preprocessing: Processing patient data, including processing missing values, outliers, standardized data, etc. Integrate data from different sources to ensure data consistency and availability. Data processing is specific to gastric cancer, such as labeling of tumor size, location, pathological type, etc.

Feature Extraction: Extracting key features from the raw data, which can include extraction of features such as texture, shape, from images or key indicators from clinical data.

Model building: Select the appropriate machine learning models, such as support vector machines, deep learning neural networks, decision trees, etc. Depending on the task, classification models (for cancer detection), regression models (for predicting survival, etc.) can be constructed. The model was trained using labeled training data to enable it to learn potential patterns and associations. Optimize the model parameters to improve the performance.

Model Testing and Evaluation: The performance of the model was evaluated using independent test datasets including accuracy, sensitivity, specificity. The robustness of the model was validated using techniques such as cross-validation.

Model Deployment: Deploy trained models into real clinical settings for the diagnosis and prediction of gastric cancer. The model can be integrated into a medical information system to support the physician decision-making process.

2.2 Traditional Machine Learning-Based Detection Approaches

2.2.1 Random Forest for Gastric Cancer Detection

To predict patient survival status for prognosis, help doctors evaluate treatment decisions, Xu et al propose a new random forest weighting method and apply it to data on gastric cancer patients coming from the Surveillance, Epidemiology, and End Results (SEER) project. The generalization ability of this weighted random forest algorithm was evaluated on 10 public healthcare datasets. Furthermore, for the same weighted pattern, the difference between using the outer pouch data (OOB) and all the training sets were explored. Next comes the specific approach Bagging tree is a means to extract the sample features. First, they used 110,697 patient cases from 1975 to 2016 from the SEER database as a sample, and then used a modified bagging tree version of random Forest to build a decision tree (DT) to extract and process the data samples. DT is then weighted by using OOB data weighted random forest to detect the generalization performance of each tree. Tree-level weighted random forest (TLWRF) was also used to optimize the problem of different OOB data on each tree. With this optimization, it is possible to predict the survival status of the patients (Xu et al, 2022).

Random survival forests (RSF) were used by Adham et al to identify important factors affecting gastric cancer outcomes. Data from 128 patients with gastric cancer were first collected through a historical cohort study conducted in Hamadan district, Iran from 2007 to 2013. The RSF is an influential related variable that can be found in the covariate set. They used this algorithm to obtain each tree with different influencing factors, and then calculated the cumulative hazard function (CHF) for each tree. The variable importance (VIMP) and Harrell's concordance index (C-index) were calculated, and the R software was used to analyze the data. The final mean C-index was calculated from the results obtained from 1000 sets of bootstrap data (Adham et al, 2017).

2.2.2 Support Vector Machine for Gastric Cancer Detection

To identify the classification of Microsatellite instability (MSI) in cancer patients, Tao Chen et al developed a model for MSI-related prediction in gastric cancer patients. The researchers first used gastric adenocarcinoma data from the Cancer Genome Atlas (TCGA) as a sample, and then normalized the data. RMS software and MATLAB software are then used to extract features and reduce redundancy. MSI was then classified using the IncRNAs model of SVM and its accuracy was evaluated by C index (Chen et al, 2019).

Lymph Node Metastasis (LNM) is an important factor affecting the life safety of patients, but several commonly used gastric imaging methods cannot achieve high sensitivity and specificity, so they cannot evaluate the status of gastric cancer lymph nodes well. Xiao-Peng Zhang et al uses support vector machine technology to solve this problem. The researchers first selected 175 gastric cancer patients who received MDCT before surgery and used univariate analysis to obtain the relationship between different characteristics of gastric cancer and lymph node metastasis. These indicators are used as input to the support vector machine and output the patient's lymph node metastasis. A 5-fold cross-validation was then used to train and test the aforementioned SVM model (Zhang et al, 2011).

2.3 Deep Learning-based Detection Approaches

2.3.1 Convolutional Neural Network for Gastric Cancer Detection

Hong Jin Yoon et al Developed an EGC detection and depth prediction model to help in the diagnosis of

EGC. The study team first divided the endoscopic maps into EGC and non-EGC using the Visual Geometry Group (VGG) -16 model. A loss function was then used to simultaneously measure classification and localization errors simultaneously, and then 11,539 endoscopic images collected were used as samples of the experiment to obtain the probability of EGC detection and deep neural network detection (Yoon et al, 2019).

To automatically detect endoscopic images of gastric cancer, Toshiaki Hirasawa et al developed a CNN. The team collected 13,584 images from 2,639 cancer lesions, and the team followed them up with a deep neural network called the Single Shot MultiBox Detector (SSD) to build this CNN algorithm. To detect the accuracy of the CNN, the team also collected 2,296 images to serve as an independent test set and apply them to the CNN. Finally, by using the input data to this model, to see whether the output of multiple input figures of the same lesion is consistent, if it is regarded as the correct answer (Hirasawa et al, 2018).

3 DISCUSSION

Although significant progresses have been achieved in the past, there are still some deficiencies in the application of AI model in gastric cancer detection:

1) Poor interpretability. In the medical field, the explanatory nature of the model is very crucial (Cheng et al, 2020, Zhang et al, 2017). Physicians need to understand the decision-making process of the model in order to trust and accept the suggestions of the model. AI models may sometimes be different from the concerns that humans need, so they are questioned by doctors and patients. To solve this problem, the AI model developed later needs to inject more domain knowledge and combine it with expert advice at the time of training, while extracting the key parts to the AI model.

2) Lack of sufficient diversity and representativeness. AI models may lack representation of various populations and different cases due to insufficient training data. This may lead to decreased performance of the model on specific patient populations or in rare cases. To address this issue, it should be ensured that the training data cover different populations, disease stages and disease types to improve the robustness and applicability of the model (Qiu et al, 2022).

3) Lack of real-time and immediate feedback: In gastric cancer detection, timely results are crucial for the treatment and decision-making process. Some AI models may have problems with slow processing and an inability to provide real-time feedback, which may affect their practical application in the clinical setting. To solve this problem, the inference speed of the model can be optimized, and techniques such as lightweight model structure or hardware acceleration can be adopted to ensure that the model achieves better performance in real-time performance.

4) Collaborative difficulties between doctors and AI models: In practical clinical scenarios, the collaboration between doctors and AI models may face communication barriers and operational difficulties. There may be uncertainty among doctors about how to understand, interpret, and integrate the output of the AI model, leading to the model's recommendations not being fully utilized. To address this problem, physician understanding of AI models can be strengthened through regular training and educational activities, and closer collaborative mechanisms can be established to ensure that doctors can fully use the information provided by the model to make more accurate diagnosis and treatment decisions.

5) Privacy and ethical issues: When using the AI model for gastric cancer detection, the personal health information and medical data of the patients are involved (Kaissis et al, 2021, Ziller et al, 2021). Protecting patient privacy is a serious challenge, especially in the context of data sharing and model deployment. To address this issue, privacy protection technologies, such as differential privacy, can be used to ensure the security of patient data. In addition, a transparent ethical framework and regulations are established to regulate the use of AI models in the medical field to balance the relationship between technological innovation and patients' rights and interests and improve public trust in AI models.

4 CONCLUSION

In this paper, a review of the detection of gastric cancer using the AI model was completed, and the discussed research method is mainly based on artificial intelligence methods. It mainly focuses on ML and DL, including CNN and RF methods. Additionally, this paper deeply discusses the shortcomings of AI prediction model and puts forward corresponding suggestions. The application of AI in gastric cancer identification has had a significant impact on the field. First of all, AI technology can improve the diagnosis rate, through automated and intelligent methods, faster analysis of large amounts of medical imaging data, to provide doctors with timely and accurate auxiliary diagnosis. Secondly, the application of AI can reduce the medical cost, reduce the burden of medical staff, improve work efficiency, while reducing the possibility of repeated examination and misdiagnosis. However, the paper also points out the shortcomings of the current model. Models that mainly focus on CNN and RF may have limitations in specific aspects, such as poor interpretability and insufficient ability to deal with uncertainty. To solve these problems, this paper puts forward the future prospect. It includes expanding the research direction of the model e.g. exploring the video dynamic detection and the introduction of recurrent neural network. They can further improve the performance and applicability of the model.

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