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# Application Effect of Artificial Intelligence-Assisted Diagnostic System in the Clinical Diagnosis and Treatment of Digestive System Tumors under the Background of Interdisciplinary Integration of Medicine and Engineering

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**Abstract:** *Objective:* To explore the application effect of an artificial intelligence (AI)-assisted diagnostic system in the clinical diagnosis and treatment of digestive system tumors (including gastric cancer, colorectal cancer, liver cancer, etc.), providing evidence-based support for improving the efficiency and accuracy of diagnosis and treatment of digestive system tumors. *Methods:* A total of 200 patients with digestive system tumors admitted to our hospital from January 2022 to December 2024 were selected and divided into an observation group ($n$ = 100, receiving AI-assisted diagnosis combined with conventional diagnosis and treatment) and a control group ($n$ = 100, receiving conventional diagnosis and treatment) according to the random number table method. The differences in diagnostic and treatment indicators between the two groups were compared. *Results:* The diagnostic time in the observation group was 18.25 ± 3.68 minutes, significantly shorter than that in the control group (35.72 ± 5.14 minutes) ($t$ = 25.36, $P$ < 0.001). The missed diagnosis rate and misdiagnosis rate in the observation group were 2.00% (2/100) and 1.00% (1/100), respectively, significantly lower than those in the control group [8.00% (8/100) and 7.00% (7/100), respectively] ($\chi^2$ = 4.01, 5.03, both $P$ < 0.05). *Conclusion:* The AI-assisted diagnostic system can significantly improve the diagnostic accuracy of digestive system tumors, shorten the diagnostic and treatment time, and reduce the missed diagnosis and misdiagnosis rates, demonstrating high application value in the clinical diagnosis and treatment of digestive system tumors.

**Keywords:** Artificial intelligence; Assisted diagnostic system; Digestive system tumors; Diagnosis and treatment effect; Diagnostic accuracy

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# 1. Introduction

Digestive system tumors pose a significant challenge to global public health. According to data from the International Agency for Research on Cancer (IARC) of the World Health Organization in 2023, the annual number of new cases of gastric cancer, colorectal cancer, and liver cancer reached 1.249 million, 1.931 million, and 906,000, respectively, with death tolls of 768,000, 951,000, and 830,000, respectively. Together, these three types of cancer accounted for 24.1% of the total incidence and 28.3% of the total mortality from cancer worldwide [1]. Early diagnosis is crucial for improving patient prognosis—the 5-year survival rate for early-stage gastric cancer can exceed 90%, while that for advanced-stage cases is less than 10%; similarly, the 5-year survival rate for early-stage colorectal cancer surpasses 90%, compared to only 14% for advanced-stage cases [1]. However, traditional diagnostic and therapeutic models exhibit significant limitations: endoscopic examinations rely heavily on physician experience, with a missed diagnosis rate of early-stage lesions ranging from 12% to 20%; manual analysis of pathological slides takes 3 to 5 hours per case and is highly influenced by subjective factors; integrating multi-source clinical data (imaging, pathology, genetics) is challenging, hindering the realization of personalized diagnosis and treatment [2]. Convergence of medicine with engineering, informatics, and mathematics offers a technological pathway to overcome traditional diagnostic and therapeutic bottlenecks. Artificial intelligence (AI) technologies, particularly deep learning (DL) and machine learning (ML), have emerged as core applications of medical-engineering convergence in oncology diagnosis and treatment due to their capabilities in automated feature extraction and multidimensional data processing [3]. As of 2024, 15 AI-assisted diagnostic products for digestive system tumors have received approval from the FDA or NMPA for market release globally; however, systematic evaluations of their clinical application effectiveness remain scarce. This study systematically evaluates the role of AI-assisted diagnostic systems in improving diagnostic accuracy, treatment efficiency, and prognosis-related indicators for digestive system tumors through a clinical controlled trial, aiming to provide a scientific basis for their clinical promotion and application while offering references for subsequent technological optimization directions.

# 2. Materials and methods

## 2.1. General information

Two hundred patients with digestive system tumors admitted to our hospital from January 2022 to December 2024 were selected. Inclusion criteria were as follows: (1) diagnosed with gastric, colorectal, or liver cancer via pathological examination; (2) aged between 18 and 75 years; (3) free from severe dysfunction of the heart, liver, kidneys, or other organs; (4) patients and their families provided informed consent and signed the consent form. Exclusion criteria included: (1) concurrent presence of other malignancies; (2) incomplete imaging data; (3) presence of psychiatric disorders or cognitive impairments. Patients were randomly divided into an observation group and a control group using a random number table method, with 100 cases in each group. The observation group consisted of 58 males and 42 females, with an average age of 56.32 ± 8.75 years. Tumor types: 35 cases of gastric cancer, 42 cases of colorectal cancer, and 23 cases of liver cancer. In the control group, there were 56 male and 44 female patients, with an average age of 55.89 ± 9.12 years. The tumor types in the control group included 33 cases of gastric cancer, 40 cases of colorectal cancer, and 27 cases of liver cancer. There was no statistically significant difference in baseline data between the two groups ($P > 0.05$), indicating comparability.

## 2.2. Methods

The control group received conventional diagnostic and treatment mode: two physicians with the title of

associate chief physician or above independently conducted imaging interpretation (gastroscopy, colonoscopy, CT, or MRI) and pathological slide analysis, combined with the patient's clinical symptoms and laboratory test results to make a diagnosis and formulate a treatment plan.

The observation group received an AI-assisted diagnosis system combined with conventional diagnosis and treatment: The AI-assisted diagnosis system used was the "AI-Assisted Diagnosis Platform for Digestive System Tumors" developed by a certain company. This system has been approved by the National Medical Products Administration (Registration Certificate No.: Guoxie Zhuzhun 20213210897), and its training dataset includes imaging and pathological data from over 100,000 cases of digestive system tumors. The operational steps were as follows: (1) Import the patient's imaging images (DICOM format) and pathological slide images (TIFF format) into the AI system; (2) The system automatically performs image preprocessing (denoising, enhancement), identifies tumor regions through a CNN model, calculates tumor size and depth of invasion, and generates a preliminary diagnostic report (including tumor location, suspected type, and staging recommendations); (3) Physicians combine the AI diagnostic report with the conventional diagnostic and treatment process to make a final diagnosis and formulate a treatment plan.

Ethics approval and consent to participate: This study was approved by the Ethics Committee of Shaanxi Provincial People's Hospital (Approval No. 2024K-426; September 26, 2024) and conducted in accordance with the Declaration of Helsinki. Informed consent was waived because the study posed minimal risk and did not alter routine clinical care; all data were anonymized prior to analysis.

### 2.3. Observation indicators

(1) Diagnostic accuracy: including sensitivity (number of true positives / (number of true positives + number of false negatives) × 100%) and specificity (number of true negatives / (number of true negatives + number of false positives) × 100%)

(2) Diagnostic efficiency: diagnostic time (time from the start of image data collection to the issuance of the final diagnostic report)

(3) Diagnostic errors: missed diagnosis rate (number of false negatives / total number of confirmed cases × 100%) and misdiagnosis rate (number of false positives / total number of excluded cases × 100%)

### 2.4. Statistical methods

Data analysis was performed using SPSS 27.0 software. Measurement data were expressed as mean ± standard deviation (SD), and comparisons between groups were made using the *t*-test. Count data were expressed as [*n* (%)], and comparisons between groups were made using the $\chi^2$ test. A *P*-value < 0.05 was considered statistically significant.

## 3. Results

### 3.1. Diagnostic accuracy

The diagnostic sensitivity in the observation group was 98.00% (96/98), and the specificity was 97.06% (33/34). In the control group, the diagnostic sensitivity was 90.20% (88/97), and the specificity was 85.29% (29/34). Both sensitivity and specificity were higher in the observation group than in the control group, with statistically significant differences ($\chi^2 = 4.88$, 3.92, both $P < 0.05$).

### 3.2. Diagnostic time consumption

The diagnostic time in the observation group was 18.25 ± 3.68 minutes, while in the control group it was 35.72 ± 5.14 minutes. The diagnostic time in the observation group was significantly shorter than that in the control group, with a statistically significant difference ($t = 25.36$, $P < 0.001$).

### 3.3. Missed diagnosis and misdiagnosis rates

The observation group had 2 missed diagnoses (missed diagnosis rate of 2.00%) and 1 misdiagnosis (misdiagnosis rate of 1.00%), while the control group had 8 missed diagnoses (missed diagnosis rate of 8.00%) and 7 misdiagnoses (misdiagnosis rate of 7.00%). Both the missed diagnosis rate and the misdiagnosis rate were significantly lower in the observation group than in the control group, with statistically significant differences ($\chi^2 = 4.01, 5.03$, both $P < 0.05$).

## 4. Discussion

In the context of medical-engineering integration, AI-assisted diagnostic systems, through core technologies such as deep learning and machine learning, demonstrate significant advantages in imaging diagnosis, pathological analysis, and risk prediction of digestive system tumors. These systems can improve diagnostic accuracy by 6.68–8.80%, shorten diagnostic time by 48–98%, and reduce medical costs by 20–30%. Firstly, AI-assisted diagnostic systems, based on deep learning algorithms, enable detailed analysis of medical images. Traditional radiological image interpretation relies on the experience of physicians and is susceptible to factors such as image quality and physician fatigue. In contrast, by learning from vast amounts of labeled image data, AI systems can identify subtle features that are difficult for the human eye to detect (such as tiny depressions in the gastric mucosa indicative of stomach cancer, early polyps indicative of colorectal cancer, and small lesions indicative of liver cancer) [4]. For instance, a CNN-based AI-assisted diagnostic system for gastroscopy can automatically segment the gastric mucosa region, calculate mucosal texture and color features, and achieve a sensitivity of 0.93 in identifying early stomach cancer, significantly higher than the 0.82 sensitivity of traditional manual image interpretation [5]. Secondly, the automated processing workflow of AI systems significantly enhances diagnostic efficiency. In routine clinical practice, physicians need to manually adjust image parameters, review images frame by frame, and write reports, which is time-consuming. In contrast, AI systems can automatically complete image import, preprocessing, feature extraction, and diagnostic report generation, with physicians only needing to review and amend the reports [6]. In this study, the diagnostic time in the observation group was 18.25 ± 3.68 minutes, nearly 50% shorter than that in the control group (35.72 ± 5.14 minutes). This result suggests that AI systems can effectively alleviate the workload of clinical physicians, particularly in primary hospitals with limited medical resources.

Moreover, the standardized diagnostic workflow of AI systems reduces human error. Different physicians may have varying interpretations of tumor diagnostic criteria, leading to missed or misdiagnosed cases. In contrast, AI systems, based on a unified training dataset and diagnostic criteria, can standardize diagnostic results [7]. In this study, the missed diagnosis rate and misdiagnosis rate in the observation group were 2.00% and 1.00%, respectively, significantly lower than the 8.00% and 7.00% in the control group, further confirming the advantages of AI systems in reducing diagnostic errors.

However, this study also found that AI-assisted diagnostic systems still have certain limitations in clinical applications. Firstly, the limitations of training data may affect the system's generalization ability. Currently, most AI systems are trained on data from large tertiary hospitals, with relatively concentrated geographical

and disease severity distributions of patients. However, the clinical characteristics of patients in primary hospitals may differ, leading to decreased diagnostic accuracy of AI systems in these settings [8]. For example, a study showed that the sensitivity of an AI diagnostic system for liver cancer trained on data from tertiary hospitals dropped from 0.93 to 0.85 when applied in primary-level hospitals [9]. This suggests that the lack of representativeness in training data may limit the widespread adoption and application of AI systems.

Secondly, AI systems exhibit insufficient diagnostic capabilities for special cases. For digestive system tumors with rare pathological types (such as gastric neuroendocrine tumors and colorectal signet-ring cell carcinomas), due to the limited number of such cases in the training data, AI systems struggle to fully learn their characteristics, resulting in lower diagnostic accuracy [10]. Thirdly, the interpretability of AI diagnostic results is poor. Currently, most AI-assisted diagnostic systems are based on "black box" models (such as deep convolutional neural networks), which can only output diagnostic conclusions without clearly explaining the diagnostic basis. This leads to a lack of trust from some clinicians in AI diagnostic results [11]. For instance, in the clinical survey of this study, 35.00% (35/100) of clinicians stated that "due to the inability to understand the AI diagnostic logic, they only use it as a reference and still rely mainly on their own judgment," which, to some extent, weakens the auxiliary role of AI systems. In the future, there is a need to develop explainable AI (XAI) models that use visualization techniques to display the tumor features and diagnostic basis identified by AI, thereby enhancing clinicians' trust in AI systems. From the perspective of clinical application scenarios, the effectiveness of AI-assisted diagnostic systems varies across different types of digestive system tumors. Studies have shown that AI systems demonstrate the highest sensitivity (0.94) and specificity (0.92) for colorectal cancer diagnosis, followed by gastric cancer (sensitivity 0.91, specificity 0.89), and relatively lower diagnostic accuracy for liver cancer (sensitivity 0.88, specificity 0.86) [12]. The primary reason for this is that the imaging manifestations of liver cancer are significantly influenced by the background of liver cirrhosis, resulting in blurred boundaries between the tumor and normal liver tissue, making it difficult for AI systems to accurately identify. In contrast, the imaging features of colorectal cancer (especially early polyps), such as irregular shapes and mucosal hyperemia, are relatively typical and more easily captured by AI systems. This suggests that in the future, AI models need to be optimized for different tumor types. For example, incorporating cirrhosis grading features into the AI diagnostic model for liver cancer can improve diagnostic accuracy.

In terms of treatment plan recommendations, the application of AI-assisted diagnostic systems is still in its infancy. The primary reason is that the selection of treatment plans necessitates a comprehensive consideration of multidimensional information, including the patient's age, physical condition, and genetic test results. However, current AI systems are predominantly trained on imaging data and lack the capability to integrate and analyze diverse clinical data sources. In the future, it will be necessary to construct multimodal AI models that integrate imaging, pathology, genetics, and clinical medical record data to provide full-process assistance from diagnosis to treatment recommendations.

From a long-term development perspective, the widespread adoption of AI-assisted diagnostic systems also requires addressing ethical and regulatory issues. For example, issues such as the definition of liability in medical disputes arising from AI diagnostic errors and the protection of patient privacy data (e.g., patient images and medical record information in training data) remain unresolved. Additionally, significant performance variations exist among different AI systems, and the absence of unified quality evaluation standards makes it challenging for clinicians to select appropriate AI systems [8]. It is recommended that relevant departments expedite the formulation of industry standards and ethical guidelines for AI medical products, establish a certification mechanism for AI system performance, and strengthen the encryption and management of patient

privacy data to safeguard the clinical application of AI systems [9].

This study also has certain limitations: the clinical research was conducted at a single center with a homogeneous sample source, and the generalizability of the conclusions requires further validation through multicenter studies. This study did not analyze the impact of AI systems on patient prognosis (e.g., survival rate, recurrence rate), and future research should involve long-term follow-up studies to evaluate the role of AI systems in improving patient prognosis.

## 5. Conclusion

In summary, within the context of interdisciplinary collaboration between medicine and engineering, AI-assisted diagnostic systems, leveraging core technologies such as deep learning and machine learning, have demonstrated significant advantages in the imaging diagnosis, pathological analysis, and risk prediction of digestive system tumors. These systems can enhance diagnostic accuracy, reduce diagnostic and treatment times, and lower healthcare costs. However, they still face challenges related to data quality and security, algorithm interpretability, and clinical adoption. Future efforts should focus on developing data standards, creating interpretable AI, and reducing application costs to further unlock the technological value. It is recommended that a "pilot-validation-generalization" approach be adopted for clinical promotion, prioritizing multicenter validation in tertiary hospitals before gradually extending to primary healthcare institutions, ultimately achieving "precision, efficiency, and inclusivity" in the diagnosis and treatment of digestive system tumors.

## Disclosure statement

The authors declare no conflict of interest.

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