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Deep Fusion and Efficiency Enhancement of AI Intelligent Diagnostic System in Medical Image Processing

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Abstract

To explore the deep fusion mode of AI intelligent diagnostic system in medical image processing and its role in improving diagnostic efficiency. Method: A retrospective analysis was conducted on the data of 300 patients who underwent CT, MRI, or X-ray examinations in our hospital from January 2023 to January 2024. Among them, 150 patients were diagnosed using traditional medical image analysis methods (traditional group), and 150 patients were diagnosed using an analysis process integrated with an AI intelligent diagnostic system (AI group). Compare the diagnostic accuracy, diagnostic time, lesion detection rate, and missed diagnosis rate between two groups. Result: The diagnostic accuracy of the AI group was 94.67%, significantly higher than the traditional group's 86.67% ($P<0.05$); The average diagnosis time for the AI group was 12.3 minutes, which was significantly shorter than the traditional group's 21.5 minutes ($P<0.05$); The lesion detection rate in the AI group reached 92.37%, which was higher than the 83.59% in the traditional group ($P<0.05$); The missed diagnosis rate in the AI group was 3.34%, which was lower than the traditional group's 10.71% ($P<0.05$). Conclusion: The deep integration of AI intelligent diagnostic systems and medical image processing can significantly improve diagnostic efficiency, optimize clinical workflow, provide strong support for precision medicine, and have broad application prospects.

Keywords

AI intelligent diagnosis; Medical image processing; Deep integration; Efficiency improvement

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1. Introduction

Medical image processing has emerged as an indispensable component in contemporary medical diagnostics. Medical imaging modalities such as CT (Computed Tomography), MRI (Magnetic Resonance Imaging), and X-ray films enable the clear visualization of internal tissues, organs, and pathological changes, facilitating direct clinical assessment by physicians [1]. However, this field is confronted with two primary challenges: First, the advancement of medical equipment has led to an exponential growth in medical data, posing a significant challenge in extracting meaningful information from large datasets. Second, subtle lesions, early-stage pathologies, or those located in anatomically complex regions (such as the skull base or spinal canal) often lack obvious morphological alterations, rendering them difficult to detect [2]. Therefore, the integration of computational algorithms for automated feature extraction holds the potential to substantially reduce the time and labor associated with manual analysis, while simultaneously mitigating uncertainties introduced by human subjectivity [3].

In recent years, artificial intelligence (AI), as an emerging discipline, has attracted increasing attention and achieved numerous advancements. It primarily focuses on the fundamental theories of biological nervous systems and intelligent behaviors, along with their engineering implementations, aiming to mimic human thought processes. Through mathematical descriptions of knowledge application programs and technologies, AI endows machines with the ability to perceive environments and accomplish predefined tasks [4]. The core philosophy of AI technology lies in emulating human brain thinking patterns: by studying the learning mechanisms of human brain neurons, it develops new artificial systems that can generate corresponding outputs based on input information, without requiring explicit instructions or rules written by programmers [5]. Currently, AI-based medical imaging technologies have been widely integrated into all aspects of medical image processing: including image segmentation and registration in the preprocessing stage, tumor volume measurement and lesion localization in the lesion detection stage, as well as diagnostic assistance in the final stage. Additionally, AI has been applied to disease classification diagnosis, drug design, surgical planning, rehabilitation training, and other domains. Numerous scholars are now dedicated to leveraging AI technologies to address the challenges inherent in traditional medical image diagnostics [6].

This study investigates the application paradigm of integrating AI intelligent diagnostic systems with medical images, aiming to validate their efficacy in enhancing diagnostic accuracy for medical imaging. By comparing traditional medical image analysis with AI-integrated approaches, this research conducts multi-faceted quantitative statistical analyses to evaluate whether the system can assist healthcare professionals in reducing diagnostic time, improving lesion detection rates, and minimizing misdiagnoses and missed diagnoses—all while maintaining diagnostic reliability. The findings seek to: (1) establish a theoretical foundation for the development of AI in medical imaging; (2) provide practical insights for healthcare professionals to optimize AI technology integration.

2. General Materials and Methods

2.1. Study Cohort

This retrospective cohort study enrolled 300 patients who underwent CT, MRI, or X-ray examinations in the Department of Radiology of our institution between January 2023 and January 2024. All participants met pre-specified inclusion and exclusion criteria, as follows: Inclusion criteria: (1) Aged 18–80 years, regardless of gender; (2) Clinically suspected or confirmed pulmonary diseases (e.g., pulmonary nodules), cerebral diseases (e.g., stroke), or hepatic diseases (e.g., liver cancer); (3) Complete CT/MRI/X-ray imaging data with diagnostic quality. Exclusion criteria: (1) Images with severe artifacts (motion or metallic artifacts); (2) Suboptimal image quality (CT slice thickness >5 mm or matrix <512×512); (3) Concomitant multi-system malignancies or end-stage diseases; (4) Incomplete clinical records. Participants were randomized into two groups using a random number table: Conventional group (n=150): Diagnoses were independently performed by two senior radiologists using standard methods.AI group (n=150): Diagnoses were assisted by an AI intelligent diagnostic system, with final confirmation by radiologists. Baseline characteristics were comparable between groups ($P>0.05$): Conventional group: Mean age 58.2±10.5 years; 82 males (54.7%) and 68 females (45.3%); disease distribution: 65 pulmonary (43.3%), 45 cerebral (30.0%), 40 hepatic (26.7%). AI group: Mean age 57.8±11.2 years; 85 males (56.7%) and 65 females (43.3%); disease distribution: 63 pulmonary (42.0%), 47 cerebral (31.3%), 40 hepatic (26.7%). This study was approved by the Institutional Ethics Committee and conducted in accordance with the ethical principles of the Declaration of Helsinki. All patients provided written informed consent for the use of their anonymized imaging data in scientific research.

2.2. Methods

2.2.1. Imaging Protocols

Imaging protocols were systematically established based on disease types and clinical diagnostic requirements:

CT examinations (60%) were performed using a Siemens SOMATOM Force dual-source CT scanner with core parameters: slice thickness 1 mm, tube voltage 120 kV, and reconstruction matrix 512×512. Clinical applications included:

Low-dose thin-slice scanning (radiation dose ≤1 mSv) for pulmonary nodule screening

Non-contrast CT combined with perfusion imaging (CBF/CBV parameter analysis) for acute stroke assessment

Triphasic contrast-enhanced scanning (arterial, portal venous, and delayed phases) for liver cancer diagnosis

MRI examinations (35%) were conducted on a GE Signa Premier 3.0T superconducting MRI system, including standardized sequences: T1-weighted imaging (T1WI), T2-weighted imaging (T2WI), diffusion-weighted imaging (DWI), and susceptibility-weighted imaging (SWI). Protocol parameters: slice thickness 3 mm, field of view (FOV) 240 mm. Specific applications: SWI sequence (phase-magnitude fusion reconstruction) for cerebral microbleed detection. DWI sequence (b-value=1000 s/mm²) for early cerebral infarction diagnosis. Dynamic contrast-enhanced scanning (gadolinium-based contrast agent 0.1 mmol/kg) for hepatic focal lesion characterization. X-ray examinations (5%) were performed using a Philips Digital Diagnost system with tube voltage controlled at 70–90 kV and automatic exposure control (AEC) to ensure image consistency. Indications included: Emergency skeletal trauma assessment (fracture line identification and joint dislocation detection). Chest disease screening (e.g., pneumonia consolidation detection).

2.2.2. Diagnostic Workflows

(1) Conventional Diagnostic Workflow

Radiologists independently completed the full diagnostic process: Systematically reviewing raw images (including multi-planar reformations) to manually identify suspicious lesions; Extracting features by quantitatively measuring lesion diameter (mean of three-dimensional dimensions), density (CT value/HU), or signal intensity (T1/T2 values), and recording qualitative characteristics such as boundary morphology (clear/indistinct) and internal structure (cystic change/calcification); Performing differential diagnosis by integrating clinical data (medical history, laboratory tests, etc.); Generating narrative diagnostic reports. This workflow relied entirely on radiologists' professional experience without any computer-aided tools.

(2) AI-Assisted Diagnostic Workflow

A standardized human-machine collaborative protocol was implemented: AI Preprocessing: The system performed DICOM raw image preprocessing, including: Non-local means denoising (noise reduction >40%). Adaptive histogram equalization (contrast enhancement). Motion artifact correction (based on registration algorithms). Deep Learning Model Analysis: A cascaded deep learning framework was employed: First, the nnU-Net 3D segmentation model achieved automatic lesion segmentation (outputting 3D volume and spatial coordinates). Then, the ResNet-50 classification model performed benign-malignant discrimination (outputting malignancy probability and confidence score). The models were trained on an independently annotated dataset of 1,000 images covering 10 common lesion types (e.g., lung adenocarcinoma, metastatic liver cancer, lacunar infarction), with an 8:2 training-testing split. Structured Report Generation: The system automatically generated a structured report draft containing: Lesion localization (lung lobe/brain region/liver segment), Maximum diameter (mm), Malignancy probability (0–100%), Imaging feature descriptions (e.g., "ground-glass nodule with lobulation sign"), Differential diagnosis list (sorted by probability), Physician Review & Revision: Senior radiologists reviewed AI-generated drafts: Manually adjusting lesion segmentation contours via DICOM Viewer interface; Modifying malignancy probability thresholds (default: >70% as high-risk); Adding/removing differential diagnoses; All revisions required annotated justifications (e.g., "AI misidentified vascular cross-section as nodule"). Model Iterative Optimization: The system automatically collected physician revision data (≥50 cases monthly) to update model weights via incremental learning, prioritizing optimization for high-error categories (e.g., micro-nodules <5 mm).

2.3. Evaluation Metrics

(1) Diagnostic Accuracy: Using pathological biopsy results (82% of cases) or clinical follow-up data (imaging re-examination + laboratory tests) ≥6 months as the gold standard. Positivity criteria: malignant tumors confirmed by pathology; cerebral infarction confirmed by follow-up MRI lesion evolution.

(2) Diagnostic Turnaround Time: Total duration (in minutes) from PACS system receipt of complete imaging data to electronic report issuance, including physician review time, was accurately recorded.

(3) Lesion Detection Rate: Calculated as (number of true-positive lesions / total lesions confirmed by gold standard) × 100%. Micro-lesions were defined as: pulmonary nodules ≤5 mm, hepatic lesions ≤10 mm, cerebral microbleeds ≤3 mm.

(4) Missed Diagnosis Rate: Calculated as (number of missed lesions / total lesions) × 100%, where missed lesions were those unmentioned in initial reports but confirmed by the gold standard.

2.4. Statistical Methods

Statistical analyses were performed using SPSS 26.0. For measurement data (e.g., diagnostic turnaround time), normality was verified via the Shapiro-Wilk test, and results were presented as mean ± standard deviation ($x \pm s$). Independent samples t-tests were used for between-group mean comparisons (significance level $\alpha=0.05$). Categorical data (e.g., accuracy rates, detection rates) were expressed as frequencies and percentages, with between-group differences analyzed by chi-square test; Fisher's exact test was applied when theoretical frequencies were <5. Statistical significance was set at $P<0.05$ (two-tailed test).

3. Results

3.1. Comparison of Diagnostic Accuracy Between Groups

The Alibaba group achieved an overall diagnostic accuracy of 94.67%, significantly higher than 86.67%

Table 1. Comparison of Diagnostic Accuracy Between Groups (n=150)

Group	Overall Accuracy(%)	Pulmonary Accuracy(%)	Cerebral Accuracy(%)	Hepatic Accuracy(%)
Hepatic Accuracy (%)	86.67	84.62	86.67	90.00
AI Group	94.67	93.65	95.74	95.00
χ^2	5.143	3.892	4.102	1.667
P	0.023*	0.048*	0.043*	0.197

*Denotes statistical significance (P < 0.05)

Table 2. Comparison of Diagnostic Time Efficiency Between Groups

Group	Overall Diagnostic Time(min)	Image Analysis Time(min)	Report Generation Time(min)
Conventional Group	21.50±3.25	15.80±2.70	5.70±1.10
AI Group	12.30±2.15	4.20±0.85	8.10±1.45
t	28.634	45.217	12.883
P	<0.001	<0.001	<0.001

in the conventional group. The most pronounced improvement was observed in pulmonary disease diagnosis, with notable enhancement in cerebral disease diagnosis (both $P<0.05$). No statistically significant difference was found in hepatic disease diagnosis between groups ($P>0.05$), as shown in **Table 1**.

3.2. Comparison of Diagnostic Time Efficiency Between Groups

The AI group demonstrated a 43% reduction in overall diagnostic turnaround time and a 73% decrease in image analysis duration, both significantly shorter than the conventional group ($P<0.05$). However, the report generation phase (physician review) showed a 42% increase in processing time ($P<0.05$), as detailed in **Table 2**.

3.3. Comparison of Lesion Detection Rates Between Groups

The AI group showed higher overall lesion detection rate, as well as detection rates for pulmonary nodules, liver cancer lesions and cerebral microbleeds than the conventional group ($P < 0.05$), as shown in **Table 3**.

3.4. Comparison of Missed Diagnosis and Misdiagnosis Rates Between Groups

The AI group exhibited significantly lower missed diagnosis and misdiagnosis rates than the conventional group ($P<0.05$), as shown in **Table 4**.

4. Discussion

Medical images serve as indispensable information carriers in clinical diagnostics, encapsulating rich medical data. However, traditional medical image processing methods struggle to meet practical demands when confronted with the sheer volume and complexity of pathological changes [7]. The advancement of artificial intelligence (AI) has ushered in new opportunities for medical image analysis, with AI-powered diagnostic systems poised to accelerate technological progress and expand into adjacent domains [8]. This underscores the significance of researching AI applications in medical imaging, building on existing literature that has demonstrated the efficacy of AI-computer vision frameworks in diagnosing cranial and pulmonary disorders [9-10].

Our findings show that the AI group achieved significantly higher diagnostic accuracy than the conventional group, with the most pronounced improvements in pulmonary and cerebral disease diagnostics ($P<0.05$), alongside lower missed/misdiagnosis rates. This confirms that AI systems can effectively enhance diagnostic accuracy for common diseases. Leveraging deep neural networks, AI systems trained on massive medical image datasets excel at extracting subtle lesion features—for instance, automatically localizing pulmonary nodules and evaluating morphological, contour, density, and contextual

Table 3. Comparison of Lesion Detection Rates between Two Groups (%)

Index	Conventional Group(n=128*)	AIGroup(n=131*)	χ^2	*P*
Overall detection rate	83.59	92.37	5.291	0.021
Detection rate of micro-lesions				
Pulmonary nodules (≤5mm)	68.75	89.47	7.102	0.008
Liver cancer lesions (≤10mm)	71.43	90.91	4.026	0.045
Cerebral microbleeds (≤3mm)	65.22	86.96	5.014	0.025

Table 4. Comparison of Missed Diagnosis and Misdiagnosis Rates Between Groups

Group	Conventional Group(%)	AI Group(%)	χ^2	*P*
Missed Diagnosis Rate	10.71	3.34	6.127	0.013
Misdiagnosis Rate	8.33	2.00	5.556	0.018

attributes to assist in benign-malignant differentiation, thereby improving lung cancer detection [11].

The AI group reduced overall diagnostic turnaround time by 43% and image analysis duration by 73%, demonstrating substantial workflow acceleration. Clinically, traditional image interpretation demands intensive human resources for lesion identification [12], whereas AI's computational power enables rapid image processing, allowing radiologists to focus on treatment planning and critical decision-making. This is particularly critical for emergency care—e.g., acute ischemic stroke, where timely thrombolysis/endovascular therapy can mitigate disability [13]. Shorter diagnostic cycles also optimize resource allocation, streamline patient flows, and enhance healthcare service quality.

Notwithstanding these advantages, real-world adoption faces hurdles: Technical limitations: AI accuracy is compromised by poor image quality and rare diseases due to insufficient training data. Human-AI dynamics: Over-reliance on AI may erode clinical acumen, necessitating a balance between trusting AI suggestions and applying professional judgment. Continuous medical education on AI principles is essential. Model optimization: Develop multi-center training algorithms to improve performance on low-quality images and rare pathologies. Clinical translation: Formulate strategies for AI deployment across healthcare settings, establish tele-diagnosis platforms, and foster interdisciplinary collaboration to uplift grassroots diagnostic capabilities. Regulatory framework: Implement robust monitoring systems to ensure AI safety and efficacy.

AI-powered diagnostic systems exhibit substantial clinical value and promising prospects in medical imaging. Through algorithmic refinement, cross-disciplinary collaboration, and balanced human-AI integration, these technologies will likely revolutionize diagnostic efficiency and drive innovation in medical radiology.

Disclosure statement

The author declares no conflict of interest.

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