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Research on Teaching Strategies for Medical Image Processing Courses Enabled by Generative AI

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Abstract: With the rapid development of artificial intelligence technology, medical imaging is gradually shifting from traditional image reading to AI-centered assisted diagnosis, quantitative analysis, and intelligent workflows. Medical Image Processing, as a fundamental course supporting clinical applications of AI, plays an important role in interdisciplinary medical-engineering education. This course is typically offered to both medical and engineering students, whose differences in knowledge structure, thinking patterns, and language systems often lead to learning gaps and reduced teaching efficiency. This paper proposes a bidirectional knowledge-complementary teaching strategy for medical-engineering integration using generative artificial intelligence as a teaching support tool. It adopts "medical context – engineering context – unified expression" as the core bridge. Without replacing the teacher's dominant role, generative AI is involved in concept explanation, terminology alignment, and learning feedback, helping engineering students understand clinical contexts and diagnostic logic, and helping medical students understand AI algorithms and evaluation systems. By analyzing teaching challenges, designing classroom activities, and summarizing implementation experience, this paper examines the strategy's value in reducing interdisciplinary barriers, promoting a shared language, and improving classroom interaction. It also discusses potential risks and governance approaches of generative AI in education. Practice shows that, with proper regulation and evaluation mechanisms, generative AI can serve as an effective interdisciplinary bridge in Medical Image Processing courses, providing a transferable model for medical-engineering teaching reform.

1. Introduction

In recent years, artificial intelligence technologies such as deep learning and computer vision have made significant breakthroughs in the field of medical image analysis. Tasks such as image segmentation, registration, detection, and quantitative analysis have demonstrated remarkable potential in the auxiliary diagnosis and efficacy evaluation of various diseases. Models based on convolutional neural networks, Transformers, and multimodal learning have demonstrated performance close to that of experts in tasks such as tumor detection, organ segmentation, disease classification, and prognosis assessment under specific task settings and controlled experimental conditions [1]. In actual clinical applications, the role of medical imaging is gradually shifting from qualitative judgments based solely on the subjective experience of radiologists to quantitative analysis combined with data-driven models and intelligent auxiliary decision support [2]. This transformation has set new requirements for talents in related fields: The new generation of medical imaging professionals not only need to understand the pathological and anatomical significance reflected by the images, but also need to possess the ability to collaborate with artificial intelligence systems [3-4], including understanding the algorithm assumptions, the meaning of model outputs, and the reliability boundaries of the results. A single disciplinary background is no longer sufficient to meet the actual needs of the development of intelligent medical imaging. The cultivation of interdisciplinary talents combining medicine and engineering has become an important direction in medical education and engineering education.

Previous studies have shown that integrating AI into medical education positively impacts students' clinical perception, interdisciplinary abilities, and technical application skills [5]. The Medical Image Processing course is typically positioned at the core of interdisciplinary medical-engineering training and serves as a key transition from foundational theory to medical AI applications. It covers medical image formation principles, imaging modalities, basic processing methods, and tasks such as image enhancement, segmentation, registration, and performance evaluation. In terms of teaching objectives, it not only supports subsequent courses in medical image analysis and AI applications but also helps students understand the full chain from "clinical needs – algorithm design – result interpretation." For example, students need to understand why a segmentation algorithm is suitable for a specific organ, how its performance metrics relate to clinical decisions, and what errors or risks may arise in practice. This problem-oriented approach emphasizes method selection rather than pure implementation, aiming to help students understand the roles, limitations, and applicability of different methods in clinical scenarios and develop awareness of problem-driven decision-making in medical image analysis.

Under the training mode of medicine and engineering, medical image processing courses are often oriented to students with both medical background and engineering background. This mixed medical-engineering course provides a favourable environment for interdisciplinary communication, but it also brings significant teaching challenges. Medical students usually have a solid foundation in anatomy, pathology, and clinical diagnosis and treatment, and have an intuitive understanding of the clinical significance of medical images. However, they lack experience in mathematical modelling, algorithm abstraction, and program implementation. In contrast, engineering students have a good foundation in mathematics and programming, and can quickly understand the structure of image processing and deep learning models. However, they often lack a systematic understanding of medical terminology, disease background, and clinical application boundaries. This difference in background leads to significantly different comprehension effects of the same teaching content among different student groups. Therefore, in actual applied teaching, teachers often need to repeatedly switch the perspective of explanation within the limited class hours to simultaneously meet the learning needs of medical students and engineering students. This not only increases the teaching burden but also easily causes fragmentation of the teaching rhythm. To address this issue, this paper proposes to integrate generative AI into the teaching process in a reasonable manner. By leveraging its capabilities of quickly generating multi-angle explanations, natural language expression, and context correlation [6], it can assume the role of assisting in concept explanation and context transformation. This may, to some extent, alleviate the pressure on teachers when switching between medical and engineering contexts and help students more actively construct interdisciplinary understanding.

The teaching reform discussed in this article is not merely about expanding the coverage of knowledge; instead, it focuses on addressing the comprehension weaknesses of students from different backgrounds by providing targeted support. For engineering students, the key lies in addressing the deficiencies in their understanding of the medical context and clinical applications, and enhancing their ability to align image processing methods with actual clinical problems. For medical students, it focuses on making up for the lack of engineering abstraction and artificial intelligence method expression, and enhances their understanding of algorithm logic and evaluation methods. With this goal in mind, this paper proposes a generative AI-driven bidirectional knowledge complementation teaching strategy, and summarizes reusable classroom processes in teaching practice. At the same time, it discusses the risks and governance points in the application of generative AI in teaching.

2. Analysis of Teaching Problems

The course of medical image processing has obvious intersection characteristics in the medical and engineering integration training system. On the one hand, this intersection gives the course a higher comprehensive value, but on the other hand, the understanding gap between students with different subject backgrounds is inevitably exposed in the teaching process. From the actual classroom observations, the teaching difficulties do not stem from the students' insufficient learning comprehension ability, but rather from the differences in knowledge background and expression methods. When the same concept or method is placed in different disciplinary contexts, the focus of attention, evaluation criteria, and even the judgment of "whether it is important" will all change. This difference is manifested differently among students with an engineering background and those with a medical background, thereby forming the following two representative learning and teaching problems.

(1) For students with a background in engineering: The main challenge in the medical image processing course does not lie in understanding the algorithms, but rather in the lack of knowledge about the medical context and clinical application background. Although most students already have a solid foundation in mathematics and programming, and can quickly grasp the image processing procedures and model structures, this advantage often fails to translate into a deep understanding of the problem itself when it comes to clinical applications. Previous studies have indicated that in the teaching and research of medical image analysis, engineering researchers pay more attention to algorithm performance and implementation details, while having insufficient understanding of the clinical semantics carried by the images and the diagnostic decision-making process. This has limited the effective application of the methods in real medical scenarios [7]. Specifically, there is insufficient understanding of the clinical use of different imaging modalities, and organs or lesions are only regarded as regions of interest or labels, while ignoring their medical significance and diagnostic value. More importantly, engineering students often have difficulty aligning specific image processing tasks with the actual diagnostic decision-making process. This "context disconnection" between the algorithm and clinical practice has been regarded as one of the key factors affecting the clinical interpretability and usability of artificial intelligence medical imaging models .

(2) For students with a medical background: Compared to engineering students, those with a medical background usually have a natural advantage in understanding the medical context. They are familiar with anatomical structures, pathological changes, and clinical diagnosis and treatment procedures, and can more intuitively judge the medical rationality of imaging results. However, when the course content delves into the engineering and algorithmic aspects, this advantage often fails to sustain its level of comprehension. When medical students study medical image processing methods, they often lack a systematic understanding of mathematical models, statistical assumptions, and

algorithmic logic, and thus view the related processes as black-box operations. They focus more on the results themselves while neglecting the conditions for their formation. Furthermore, performance evaluation indicators are also one of the topics that medical students commonly find confusing. Although metrics such as Dice coefficient, IoU, sensitivity or specificity have clear statistical meanings in the engineering field [8], from the perspective of students with a medical background, these indicators are often simplified to a comparison of numerical values, making it difficult for them to further understand their key points and potential sources of error, thereby limiting in-depth discussions on the reliability and applicability range of the algorithms.

The aforementioned two types of knowledge gaps do not exist independently in the classroom; instead, they are intertwined and mutually amplified. The most direct manifestation of this is that the same term often corresponds to different understandings among different student groups. For instance, "segmentation accuracy" might mean the potential for improvement in model performance in the eyes of engineering students, while for medical students, it is more closely related to the credibility of diagnosis. Such differences in understanding will affect students' grasp of the complete problem chain, making it difficult for them to establish a coherent cognition between clinical needs, task handling, method selection, and result interpretation. This fragmented state not only increases the communication costs in the classroom but also weakens the effectiveness of cultivating students' interdisciplinary skills. This is precisely the direct motivation for this article to introduce generative AI as a bridging tool.

3. Design of Generative AI-Driven Teaching Strategy

After clarifying the understanding gap caused by the differences in medical and engineering backgrounds, the key issue of teaching reform then shifts to: How can we, within the limited class hours, simultaneously meet the different learning needs of the two types of students and avoid the teaching process from being constantly pulled apart, disassembled, or fragmented? The traditional approach often relies on individual teachers' experience, using repeated switching of teaching perspectives to bridge the differences. However, this method places a heavy burden on teachers and is difficult to replicate across different courses or teachers. Based on this, this paper attempts to introduce generative AI as a teaching support tool to participate in the bridge link in the understanding process of students, rather than assume the role of knowledge teaching or answer providing. It is important to note that the introduction of generative AI is not driven by the pursuit of technological novelty. Instead, it stems from the practical observations made during daily teaching: when students have difficulty transcending the disciplinary context, if there is a tool that can help them quickly obtain an alternative perspective of explanation, perhaps more classroom energy can be devoted to discussions and reflections rather than remaining at the level of concept clarification. At the same time, teachers still bear the core responsibility of guiding and calibrating, ensuring that students' understanding is not replaced by the tool but is gradually deepened.

Under the above teaching approach, if the students' understanding process is not further dissected, interdisciplinary discussions are still likely to remain superficial. Taking this into account, this article proposes a relatively stable bridging process, which can be roughly summarized into the following three steps:

(1) The first step is "two-context explanation". During this stage, the teacher guides the students to obtain explanations in both the medical context and the engineering context for a particular key concept or task. For instance, regarding the concept of "image segmentation", in the medical context, more emphasis is placed on its clinical significance in organ delineation and lesion localization, while in the engineering context, the focus is on the model structure, loss function and performance indicators. At this stage, generative AI is mainly used to generate comparative explanations, helping

students quickly perceive the differences in attention between the two contexts.

(2) The second step is “alignment of terms and concepts”. After obtaining the bilingual explanations, students often realize that seemingly different expressions actually refer to the same core issue. The focus of this stage of teaching is not on memorizing terms, but on understanding the mapping relationship. For instance, “diagnostic reliability” might be frequently mentioned in the medical context, while in the engineering context, it is more often reflected through indicators such as sensitivity, specificity or stability. Through comparative analysis, students gradually establish a cross-contextual conceptual network.

(3) The third step is “common language production”. At this stage, students are required to formulate a unified statement in their own words, meaning to incorporate both medical significance and engineering conditions within the same explanation. This step is often the most challenging, but it is also where the real understanding takes place. The unified expression does not aim for perfection or standardization, but rather emphasizes logical consistency and semantic completeness. After repeated attempts, students will often realize that interdisciplinary understanding does not simply combine the two sets of statements together, but rather requires them to carefully reconsider “how I should think and how I should express it”.

To prevent the misuse or incorrect application of generative AI in teaching, this teaching strategy has been implemented with clear organizational principles and usage guidelines. Among them, the principle of “thinking first, then seeking help” is the most fundamental one. Before using the generative AI, students are required to first present their own understanding or judgment, even if it is not yet mature. The purpose of this requirement is to preserve the original cognitive trajectory of the students, making subsequent comparison and correction meaningful. Furthermore, for key concepts and conclusions, verification and calibration steps are incorporated into the teaching process. The explanations provided by generative AI are not regarded as the correct answers directly; instead, students need to refer back to textbooks, classroom lectures, or authoritative materials provided by teachers for verification. Through this approach, students gradually develop a rational understanding of the boundaries of generative AI's capabilities, rather than blindly trusting it.

4. Classroom Implementation Design

After clarifying the functional positioning and overall teaching strategy of generative AI in the course, the real issue is not whether it is feasible, but how to implement it. In a course like medical image processing, which inherently has a high cognitive load, any teaching reform that remains at the conceptual level is likely to fail in the actual classroom. Therefore, this study did not attempt to design a highly procedural and strictly fixed teaching process. Instead, it focused on several core teaching activities to explore how generative AI can be integrated into the classroom. In practice, the emphasis was not on whether students would use AI, but on whether the way students understood things had changed.

In the classroom implementation, the “concept bridging cards” were introduced as a structured learning activity to support students in achieving the explicit expression of interdisciplinary understanding. In the classroom, a key concept or task that frequently occurs in medical image processing and is prone to causing misunderstandings is usually selected as the input. For example, image resolution, noise and artifacts, the meanings of common segmentation evaluation indicators, or the judgment of the rationality of deformation in medical image registration, etc. After selecting the key concepts, the teacher first guides the students to initially break down the concepts using generative AI, but clearly limits the output range of the AI: First, explanations from a medical context, emphasizing the practical significance of the concept in image interpretation, disease identification, or clinical decision-making; second, explanations from an engineering or algorithmic context, focusing on its mathematical definition, model assumptions, or computational logic; third, summarizing common misunderstandings in the class, such as simply equating index values with clinical outcomes, or ignoring the impact of imaging conditions on algorithm performance, etc. The output of the generative AI is only used as reference materials, not as the standard answer.

Based on this, students need to complete their own “bridging card”. The bridging card is usually divided into three columns: medical meaning, engineering expression, and unified presentation. For students with a background in engineering, the filling process often reveals their lack of familiarity with the clinical context. For instance, they may not be able to clearly understand the actual value of a certain indicator's improvement in the diagnostic process. However, for students with a medical background, it is more likely that they will have ambiguous, empirical, or even step-over descriptions in the engineering expression section. It is precisely this incompleteness and asymmetry that serves as the crucial starting point for classroom discussions. Table 1 presents examples of bridging cards assisted by generative AI, illustrating the interdisciplinary knowledge complementation process of the concept of noise and artifacts.

Table 1: Examples of Bridge Cards Assisted by Generative AI: Interdisciplinary Knowledge Bridging for Noise and Artifact Issues

Dimension	Medical Context (Clinical Supplement)	Engineering / AI Context (AI Supplement)	Unified Expression
Concept Definition	Noise: reduced image visibility and loss of fine details; Artifact: abnormal structures or boundary displacement	Noise: random perturbations and decreased signal-to-noise ratio (SNR); Artifact: systematic errors and structural distortion	Noise = random disturbances causing reduced visibility; artifacts = systematic errors introducing false structures or spatial bias
Typical Scenarios	Noise: low-dose imaging, weak signal acquisition; Artifacts: patient motion, respiration, swallowing	Low-signal acquisition; undersampled reconstruction; over-enhancement during post-processing	“Unclear” vs. “misleading” images correspond to specific stages of the acquisition − reconstruction − post-processing pipeline
Risks	Noise: increased risk of missed diagnosis; Artifacts: false positives and localization errors	Impact on threshold-based decisions, boundary extraction, and quantitative measurements	Increased noise → higher miss rate; increased artifacts → misclassification and localization errors
Processing Trade-offs	Noise suppression may blur anatomical boundaries; artifact reduction may introduce new distortions	Denoising leads to detail loss; artifact suppression increases model sensitivity and computational cost	Noise reduction must preserve boundaries; artifact suppression requires identifying the root cause and controlling secondary distortions
Student Tasks	Engineering students: describe diagnostic impact using clinical terminology	Medical students: identify problematic pipeline stages using engineering concepts and explain trade-offs	One-sentence integrated statement: clinical impact + engineering cause + trade-off rationale

If the bridging card is more of a static form of explicit understanding, then the inter-transformational questioning constitutes the most interactive part of the class. This part does not aim for a large number of questions; rather, it emphasizes whether the questions are precise and truly touch upon the students' cognitive weaknesses. When answering inquiries from engineering students, teachers often deliberately avoid delving into the technical details of the algorithms. Instead, they constantly shift the discussion back to clinical scenarios, such as: “How would this result be used in the actual diagnostic process?” “If this indicator improves but the computational cost significantly increases, would the clinic be willing to accept it?” These questions do not always have a definitive answer, but they can force students to step away from a purely technical perspective and re-examine the underlying assumptions and boundaries of the methods. Correspondingly, when addressing medical students, the questions tend to focus more on engineering assumptions and sources of uncertainty. For instance, when discussing the segmentation results, the teacher might further ask: “What are the underlying assumptions on which this judgment is based?” “Do the errors mainly come from the model itself or the quality of the data?” Through this approach, students gradually realize that the imaging results are not absolutely objective but are the outcome of a series of technical choices and trade-offs.

During the final assessment stage, the course deliberately included sections that restricted the use of generative AI, in order to test whether students had truly internalized the interdisciplinary understanding ability. The assessment methods included random oral explanations, contextualized concept transfer questions, etc. Students were required to independently complete the entire process from problem understanding to method selection and then to result explanation in a new problem context. In practice, it can be observed that some students, after losing the assistance of AI, actually become more cautious and pay more attention to the logical consistency of their expressions. This change itself is an important indicator of the achievement of the teaching goals.

The introduction of generative AI inevitably brings about risks. This study does not shy away from these issues but instead attempts to constrain them through institutional design. Regarding the factual errors that AI may produce, it clearly stipulates that key concepts and conclusions must be verified against the authoritative materials provided in textbooks or by teachers; regarding the issue of excessive reliance, a usage principle of “answer first and then seek help” is set, and AI intervention is explicitly prohibited in certain classroom sessions; in terms of academic integrity, students are required to briefly explain the way and scope of AI usage in their assignments.

5. Conclusions

Looking back at the entire teaching implementation process, the differences in medical and engineering understanding that emerged in this course were not problems of individual students, but a structural phenomenon. In response to this reality, this article attempts and practices a “two-way knowledge complementation” teaching approach supported by generative AI. The research has found that, under the condition where teachers take the lead, the standardized use and evaluation mechanism are coordinated, generative AI is not an interfering factor that weakens the depth of learning. Instead, it can become an important tool for promoting interdisciplinary understanding. Through the combination of concept bridging cards, inter-translational questioning, and process-based evaluation, engineering students gradually learn to examine technical solutions from the perspective of clinical needs, and medical students also begin to be able to explain the rationality and limitations of image processing methods in engineering language. More importantly, a shared discussion language gradually emerged in the classroom, enabling students from different backgrounds to engage in communication around the same issue. However, this teaching strategy is not static. Different course contents and different student structures will pose new requirements for the usage of generative AI. With the support of standardization, verification and evaluation, this strategy can provide a transferable teaching path for interdisciplinary courses in medicine and engineering, and help engineering students better understand clinical issues, and medical students better understand artificial intelligence methods.

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