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AI-Powered Medical Image Processing for Data-Driven Learning in Engineering Education

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Abstract

This evidence-based paper describes a project-based learning course on how engineers analyze and interpret medical images, offering new ways to extract meaning from complex visual data. As AI-powered imaging tools—such as convolutional neural networks (CNNs), segmentation models, and vision transformers—become increasingly accessible, they also present a powerful opportunity for integrating authentic, data-rich experiences into undergraduate education. This study introduces a project-based learning (PBL) framework that positions AI-assisted medical image processing as a catalyst for developing students' data science, analytical reasoning, and interdisciplinary problem-solving skills. The main objective is to help students understand how AI can enhance image interpretation, automate diagnostic workflows, and bridge the gap between data analysis and clinical decision making.

Within this framework, students engage in open-ended projects using real or simulated medical imaging datasets such as ultrasound, MRI, or endoscopic scans. They apply AI methods to identify regions of interest, classify tissue patterns, and visualize abnormalities through segmentation and reconstruction tasks. Rather than using AI as a "black box," students examine how training data, model structure, and interpretability affect performance and ethical implications in healthcare contexts. This process deepens their understanding of both machine learning principles and biomedical imaging fundamentals.

The learning progression follows three stages. In Phase 1: Image Inquiry, students define clinically relevant questions and preprocess imaging data. Phase 2: AI-Assisted Processing introduces supervised and unsupervised learning models for segmentation, enhancement, and anomaly detection, supported by visual feedback and confidence metrics. Phase 3: Interpretation and Communication focuses on presenting findings through annotated images, dashboards, and short technical reports enhanced by AI-generated visual summaries.

An initial implementation is carried out on a multidisciplinary undergraduate course with 30 students. Early pilot results suggest that AI-powered medical image processing improves engagement, conceptual understanding, and metacognitive reflection. By embedding AI-driven imaging into data science education, this framework connects computation and visualization, preparing students for the next generation of data-informed healthcare engineering.

Introduction

Artificial intelligence (AI) and machine learning (ML) continue to reshape how modern engineers engage with visual information, transforming industries ranging from biomedical diagnostics to surgical navigation and telemedicine [1]. As clinical workflows increasingly rely on high-throughput imaging, automated segmentation, and data-driven decision support, the need for engineers who understand how to design, evaluate, and apply AI models has intensified [2]. This trend is reflected in national STEM reports and engineering accreditation priorities, which call for the integration of computation, data interpretation, and interdisciplinary reasoning into undergraduate programs [3]. Yet despite clear workforce demand, AI remains unevenly incorporated into engineering curricula—particularly when it comes to hands-on, real-world applications involving medical imaging [4].

A primary challenge lies in the gap between conceptual instruction and experiential engagement. Many programs introduce machine learning through abstract exercises, simplified datasets, or closed-end assignments, leaving students without exposure to noisy, imperfect, or clinically meaningful imaging streams [5]. This disconnect is significant, because medical images—such as MRI volumes, ultrasound panels, and endoscopic sequences—provide a rich platform for teaching core engineering competencies including instrumentation awareness, signal interpretation, visualization, and data-driven inference [6]. In addition, medical imaging tasks foreground uncertainty, error propagation, and ethical responsibility—dimensions often overlooked when AI is treated as a purely computational topic [7].

Open-source tools now provide unprecedented opportunities to bring state-of-the-art medical AI methods into undergraduate classrooms. Frameworks such as MONAI allow learners to experiment with segmentation, enhancement, and registration pipelines that once required specialized expertise [8]. Object detection architectures like the YOLO family support dynamic tissue tracking and anomaly localization, illustrating how classification translates into clinical relevance [9]. Three-dimensional reconstruction approaches—including Structure-from-Motion, Neural Radiance Fields, and Gaussian Splatting—enable students to explore anatomy spatially using monocular input data [10]. These tools represent the leading edge of medical image computing and offer powerful platforms for learning when embedded within structured and supportive instruction [11].

A growing body of engineering educational research supports the use of project-based learning (PBL) as a mechanism for meaningful AI integration [12]. PBL emphasizes inquiry-driven experimentation, iteration, and personal responsibility for outcomes—features shown to deepen conceptual transfer and retention [13]. Biomedical-focused PBL settings further challenge students to synthesize domain knowledge across engineering, imaging science, and basic physiology [14]. Recent studies document gains in student confidence, collaborative practice, and creative problem-solving when AI pipelines are applied to real datasets rather than textbook examples [15]. These findings are reinforced by metacognition-focused research demonstrating that reflective practice helps students internalize the reasoning behind modeling decisions and performance assessment [16].

Importantly, PBL-centered AI instruction aligns with calls across ASEE, ABET, and NSF-supported initiatives to produce engineers capable of navigating both digital and physical systems [17]. Medical AI projects require students to examine visual cues, interrogate model assumptions, and iterate when initial attempts fail—skills essential in clinical and translational engineering contexts [18]. Further, student-reported reflections show that working with real-world imaging data, rather than pre-cleaned datasets, encourages persistence, curiosity, and a growth mindset toward unfamiliar tools and methods [19]. These outcomes are especially valuable for broadening participation, as students with varying backgrounds can contribute meaningfully through interpretation, data curation, visualization, or coding [20].
Despite these promising developments, accessible, semester-long frameworks integrating AI-based medical imaging into undergraduate education remain rare. Most published implementations focus on graduate-level coursework, specialized electives, or short demonstration labs [21]. Undergraduate students often reach senior design without meaningful exposure to imaging modalities or AI-driven analysis workflows [22]. As a result, they enter research or industry roles unprepared to engage with the data-rich environments that characterize modern healthcare engineering [23].

To help address this curricular shortfall, this paper introduces a multidisciplinary, project-based learning model designed to leverage medical imaging as a catalyst for developing AI fluency and engineering judgment [24]. Students employ segmentation, classification, and 3D reconstruction algorithms on real and simulated imaging datasets, analyze algorithmic limitations, and reflect on both technical challenges and ethical considerations [25]. Learning artifacts—including engineering notebooks, performance logs, and survey data—provide insight into how AI imaging influences student awareness, skill trajectories, and interdisciplinary integration [26]. The overarching goal of this work is to explore how AI-powered medical imaging experiences can improve students' understanding, confidence, and analytical reasoning as future engineers [27]. Early evidence from our pilot cohort indicates that embedding AI tools into biomedical image workflows can enhance conceptual learning, increase engagement, and prepare students to navigate emerging careers at the intersection of data science and healthcare innovation [28], [29], [30].

Methods

The study draws observations from the computer vision team in the Flexible AI-enabled Mechatronic Systems Lab (FAMS), where students engaged in semester-long and project-based development on various AI computer vision models in medical imaging. Within this setting, three contemporary topics are selected to be the focuses for the team: Medical Open Network for Artificial Intelligence (MONAI), EndoGaussian, and YOLO with heatmap.

MONAI was adopted as the framework for clinical imaging pipelines for data handling, training, and evaluation, involving tasks such as segmentation and enhancement [31]. YOLO with heatmap was selected to support region-of-interest localization while providing a lightweight interpretability mechanism that links predictions to salient image regions [32], [33]. EndoGaussian was used to represent emerging 3D reconstruction and visualization approaches, allowing students to reason about anatomy spatially from monocular endoscopic sequences [34]. Taking these three topics together, they offer complementary coverage across pixel-level modeling (MONAI), object-level localization with visual explanation (YOLO with heatmap), and three-dimensional spatial understanding (EndoGaussian), forming a cohesive and comprehensive scope for the team's projects.

The computer vision team in FAMS consisted of 12 students with academic backgrounds spanning computer science, electrical and computer engineering, and mathematics. The team included six returning members and six new members who joined this semester. Among the returning members, two had participated for three consecutive semesters and four had participated for two semesters, providing continuity in tooling, documentation practices, and experimental conventions. The 12 members included four graduate students and eight undergraduate students. Graduate and undergraduate members engaged in largely similar responsibilities, including literature review, dataset preparation, model implementation, training, and evaluation. Task assignments were determined primarily by prior experience and research interests rather than academic standing. This mix of disciplinary perspectives and membership seniority supported both onboarding and sustained progress across the semester timeline.

The team followed a structured weekly workflow to support steady progress throughout the semester. During the first two weeks, members focused on literature review and scoping, reviewing prior work to define an appropriate project direction and semester milestones. After this onboarding period, the team met weekly and members took turns to share progress and key findings from the previous week; the group then discussed results, addressed technical blockers, and adjusted goals or pacing when needed. As the technical scope stabilized, members were divided into subteams aligned with the three focus areas so that development could proceed in parallel while maintaining shared expectations for evaluation and documentation. To ensure continuity and accountability, meeting minutes were taken by a different member each week and documented current progress, discussion outcomes, and next-step task assignments. Outside of meetings, each member contributed approximately four hours per week to work on the assigned tasks.

To enable hands-on experimentation and benchmarking, the team conducted targeted dataset searches and identified suitable public tumor image and video repositories, which were then supplemented with collaborator-provided material. Public sources included the Endoscopic Bladder Tissue Classification dataset accessed via Kaggle [35], which provides labeled endoscopic tissue images suitable for classification and localization experiments, as well as the PolypGen (2021) dataset [36], a multi-center colonoscopy collection that supports polyp detection and segmentation studies. To broaden coverage and support reproducibility, additional datasets and reference downloads were obtained through the NIH Common Fund Data Ecosystem (NIH Data Commons) [37] and established endoscopy dataset portals, including CVC-ColonDB [38] and official PolypGen hosting pages. In addition to public data, a subset of de-identified clinical examples was provided by Dr. Philip Zhao (NYU Langone) under appropriate data-use permissions, which allowed the team to validate workflows on clinically sourced samples alongside benchmark datasets. Across sources, datasets were documented with provenance, modality, and intended task use, then organized into a shared repository prior to preprocessing and model training.

1. Mixed method analysis

To capture a holistic view of student learning and team dynamics, the study employed a mixed-method assessment approach combining quantitative peer evaluation from CATME with qualitative self-reported reflections collected through the course feedback survey. The CATME instrument was administered mid-semester and provided structured peer ratings across dimensions such as contribution, teamwork, communication, and dependability. These numeric scores were expanded with open-ended comments that offered contextual insight into group interactions, interpersonal support, and perceived areas for improvement among teammates. Complementing these peer perspectives, the end-of-semester course feedback survey gathered student reflections on their personal learning progress, confidence with soft robotics tools and processes, and overall experience working within an interdisciplinary project environment. Closed-ended questions enabled broad measurement of trends in skill development, while open responses revealed individual reasoning, challenges, and moments of conceptual growth. Together, these instruments enabled triangulation between how students viewed their own development and how their peers experienced their contributions, producing a more nuanced understanding of both technical learning and collaborative engagement.

Results

1. CATME (Comprehensive Assessment of Team Member Effectiveness) survey

Figure 1 presents a bar chart summarizing students' perceptions across five teamwork and learning dimensions: Contribution**,** Team Interaction**,** Keeping on Track**,** Expected Quality**,** and

Having KSAs (Knowledge, Skills, and Abilities). For each category, the blue bars represent the mean rating, while the red bars indicate the standard deviation.

Across all dimensions, mean scores are consistently high, ranging from approximately 4.0 to 4.3 on a five-point scale, suggesting generally positive student experiences. The standard deviations remain relatively stable across categories, clustering around 2.0, indicating moderate variability in student responses. Overall, the figure suggests strong perceived performance in teamwork effectiveness and individual preparedness, with similar levels of response dispersion across all measured areas.

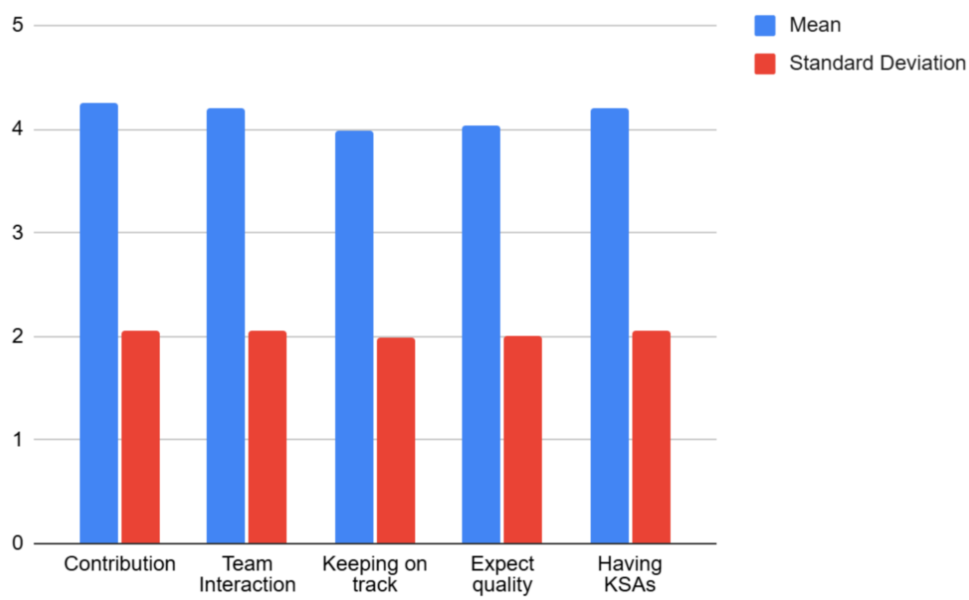


Figure 1: CATME survey results

2. Learning survey

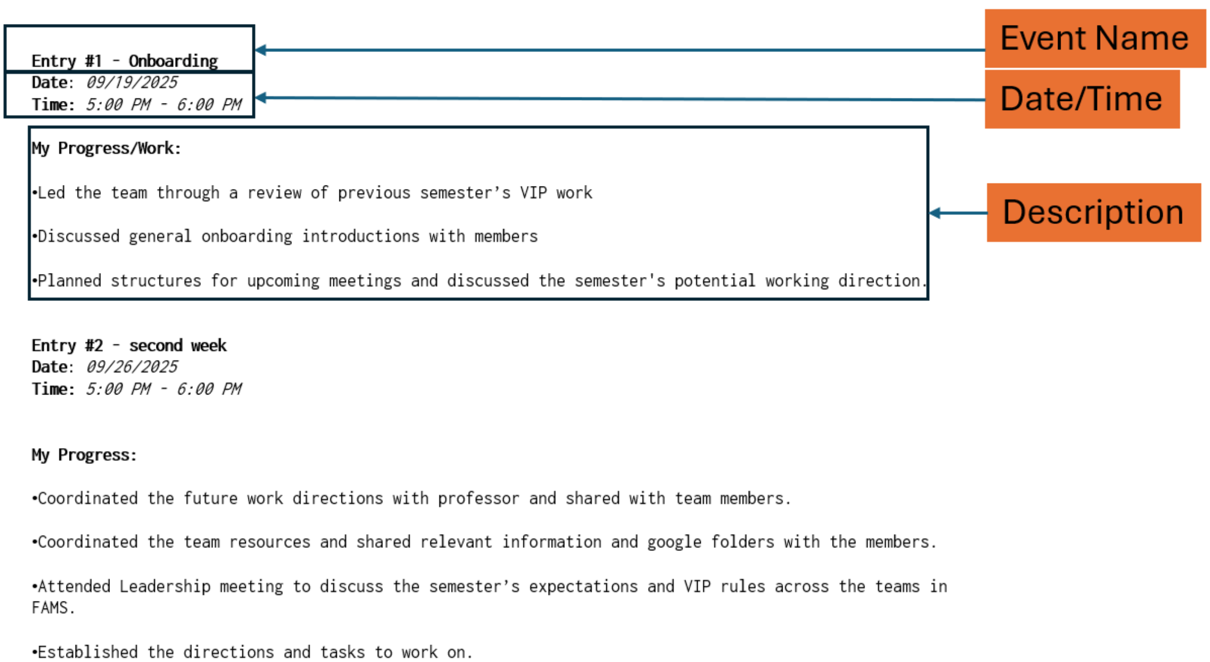
The reflections from Student A and Student B together illustrate meaningful learning gains in medical imaging and computer vision, while also revealing differences in depth, confidence, and levels of system integration.

Student A, "This semester, I learned **how to translate computer vision research into practical**, working pipelines for medical imaging. I gained experience in literature review, dataset evaluation, and implementing end-to-end systems using deep learning. I worked extensively with object detection models, heatmap generation, and visualization techniques to highlight regions of interest in endoscopic images. I also **learned how preprocessing, confidence-based reasoning, and structured outputs (JSON/CSV) improve interpretability and reproducibility**, and how to iteratively prototype before scaling to 3D or video-based approaches."

Student B, “In this semester, **I sort of learnt the fundamentals of MONAI such as its different use cases when it comes to medical imaging**. This could include the particular functions I looked more into, including performing either 3D or 2D medical segmentation/slicing given an image scan or using MONAI’s GRADCAM feature to perform gradient based classification on areas of the organ such as tumors. Although an implementation is still being worked on, given a set of image dataset, and training it with a model to **perform tumor classification is feasible**.”

3. Engineering notebook

Here is one example on how the students use an engineering notebook to document the learning process.


Entry #1 - Onboarding
Date: *09/19/2025*
Time: *5:00 PM - 6:00 PM*

My Progress/Work:

•Led the team through a review of previous semester’s VIP work

•Discussed general onboarding introductions with members

•Planned structures for upcoming meetings and discussed the semester's potential working direction.

Entry #2 - second week
Date: *09/26/2025*
Time: *5:00 PM - 6:00 PM*

My Progress:

•Coordinated the future work directions with professor and shared with team members.

•Coordinated the team resources and shared relevant information and google folders with the members.

•Attended Leadership meeting to discuss the semester’s expectations and VIP rules across the teams in FAMS.

•Established the directions and tasks to work on.

Figure 2: Detailed engineering notebook with standardized format

4. Image analysis results

This section presents a subset of representative visual results produced during the semester to illustrate progress in implementing and evaluating medical imaging workflows. The results include outputs from the MONAI-based classification and visualization pipeline, along with 3D reconstruction examples generated using a COLMAP structure-from-motion baseline to support reconstruction analysis while EndoGaussian development remained ongoing.

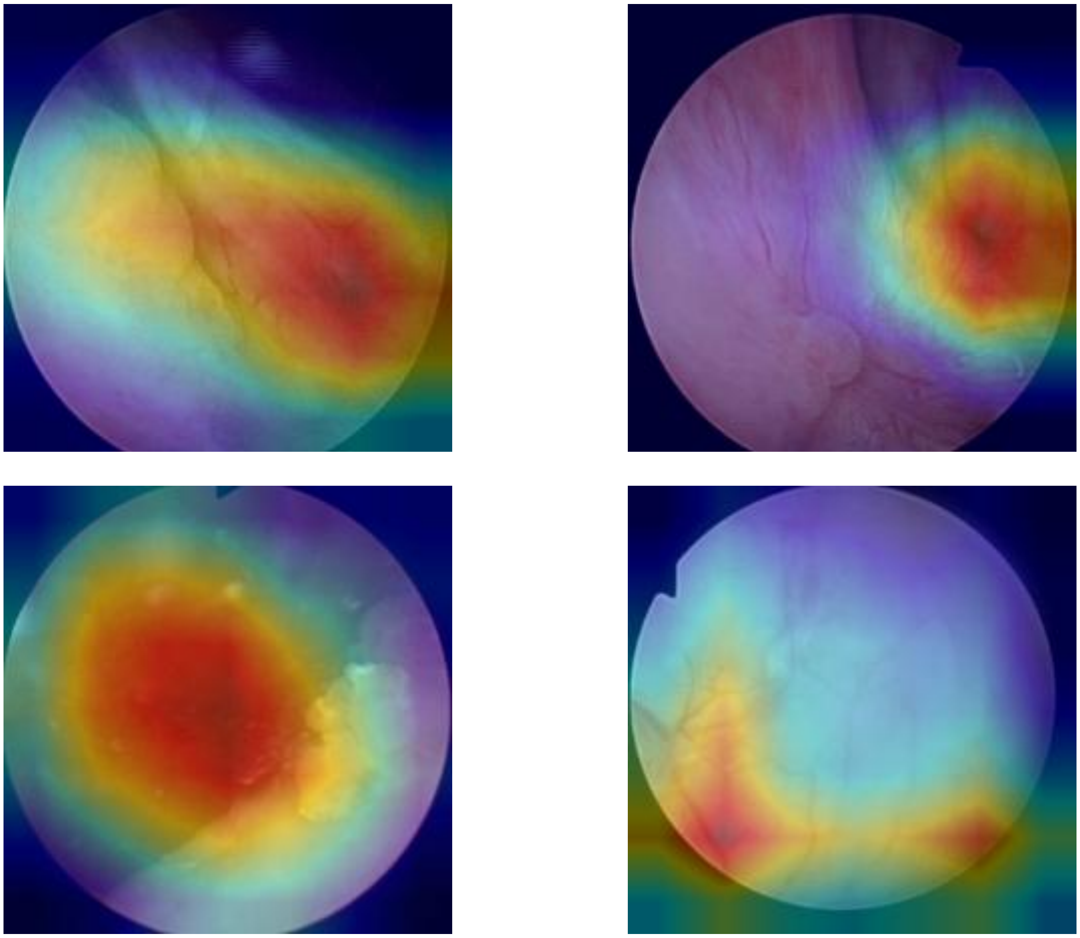


Figure 3: MONAI CAM heatmap overlays for HGC, LGC, NST, and NTL samples

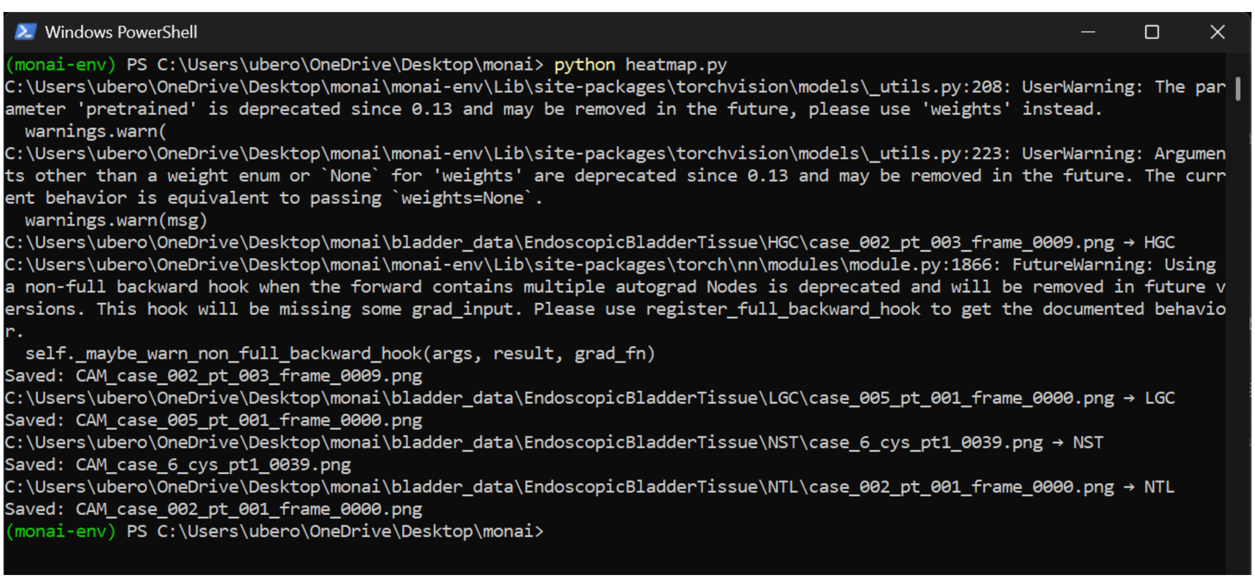


Figure 4: MONAI log panel showing inference and heatmap generation.

Students implemented a MONAI-based pipeline to train a ResNet classifier that distinguishes four bladder endoscopy tissue classes: high-grade carcinoma (HGC), low-grade carcinoma (LGC), non-suspicious tissue (NST), and no tumor lesion (NTL). Figure 2 shows the team's execution log, where the workflow runs end-to-end from inference through heatmap generation and saves class activation map outputs for representative frames. Building on this pipeline, the team produced the heatmap overlays shown in Figure 1, which serve as concrete learning artifacts that connect model predictions to visual evidence in the input images.

In **Figure 5**, the activation patterns concentrate within the endoscopic field of view and form localized regions rather than spreading uniformly across the frame, suggesting that the classifier relied on spatially specific cues when making predictions. The team used these heatmaps to interpret model behavior and to compare whether highlighted regions aligned with tissue structures of interest or reflected imaging artifacts such as illumination gradients and scope boundaries. Alongside these qualitative outputs, the run summarized in Figure 2 reports a 100% classification rate for the evaluation used in that experiment; while this value depends on the selected split and sample size, it indicates that students successfully trained and validated a working classification and interpretability pipeline within the semester setting.

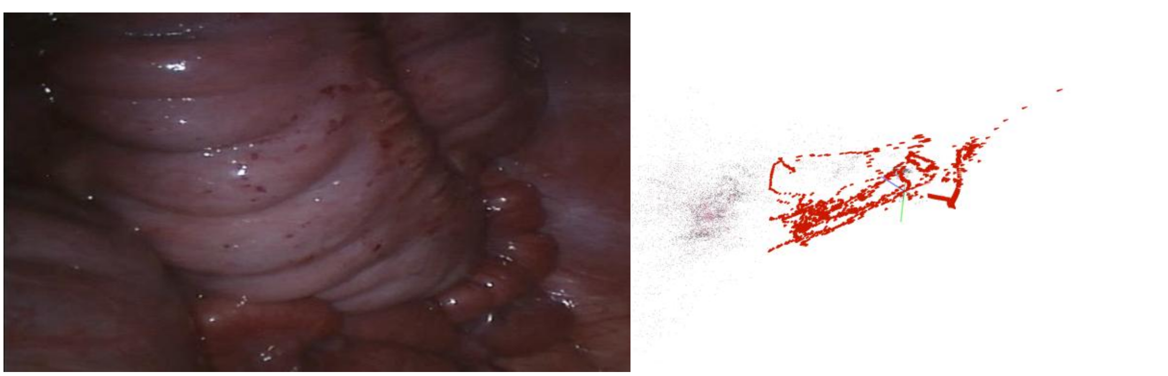


Figure 5: Endoscopic input image used for 3D reconstruction and Sparse Reconstruction

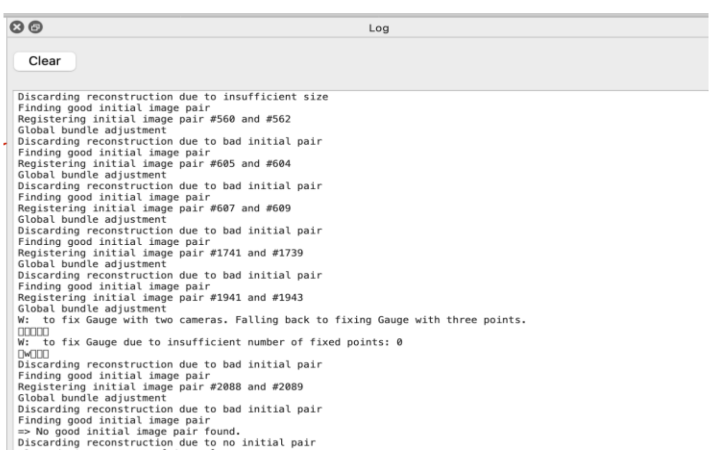


Figure 6: 3D reconstruction log panel

Using COLMAP, students implemented a structure-from-motion pipeline on a medical imaging dataset consisting of 2855 sequential frames. Feature extraction and matching completed successfully, generating 38662 sparse points, yet the resulting sparse reconstruction was incomplete and fragmented. Log outputs indicated repeated failures in identifying a stable initial image pair, as well as insufficient viewpoint diversity for global bundle adjustment. These limitations were attributed to low-texture anatomical surfaces, specular reflections, and narrow camera motion typical of clinical imaging data. Rather than treating the output as a failure, students used this result to analyze the assumptions underlying 3D reconstruction algorithms and to reflect on the importance of data acquisition conditions when applying AI tools to medical imaging.

Taken together, the MONAI heatmap visualizations and the 3D reconstructions provide complementary evidence of student learning at both the frame and sequence levels. The MONAI outputs connect predictions to localized image evidence, encouraging students to interpret model behavior rather than relying on accuracy alone. The COLMAP results extend this analysis to multi-view sequences and require reasoning about viewpoint changes and feature consistency across frames. Together, these artifacts indicate that students not only implemented end-to-end pipelines but also practiced visualization-centered evaluation and spatial reasoning on endoscopic data.

Discussion

The results of this study indicate that AI-powered medical image processing can serve as an effective anchor for data-driven learning in undergraduate engineering education. By engaging students with authentic medical imaging datasets and contemporary AI tools, the proposed project-based framework enabled learners to move beyond abstract algorithm implementation toward deeper reasoning about data quality, model behavior, and interpretability. Rather than treating AI models as black-box predictors, students were required to interrogate why models succeeded or failed, which strengthened both conceptual understanding and analytical judgment.

One key observation was the educational value of exposing students to imperfect imaging data. Across segmentation, detection, and reconstruction tasks, students encountered challenges such as low texture regions, specular reflections, motion blur, and limited viewpoint diversity—conditions rarely present in curated classroom datasets. These limitations prompted students to reflect on the assumptions embedded in AI algorithms and to recognize that model performance is strongly influenced by data acquisition conditions. As demonstrated in the 3D reconstruction experiments, incomplete sparse point clouds were not interpreted as technical failure, but as opportunities for critical analysis of algorithmic constraints and real-world applicability.

The selection of MONAI, YOLO with heatmaps, and EndoGaussian proved effective in supporting layered learning outcomes. MONAI introduced students to clinical imaging pipelines and reinforced core machine learning concepts such as preprocessing, training, and evaluation. YOLO-based localization with visual heatmaps helped bridge model prediction and interpretability, enabling students to reason about what image features influenced decision-making. EndoGaussian and structure-from-motion pipelines extended this learning into spatial reasoning, allowing students to conceptualize anatomy in three dimensions. Together, these tools provided complementary perspectives on pixel-level, object-level, and scene-level understanding.

Survey responses and engineering notebooks further suggest that the framework supported metacognitive development. Students frequently reflected on uncertainty, parameter sensitivity, and performance trade-offs, demonstrating awareness of how modeling decisions influenced outcomes. These reflections align with prior research showing that open-ended, data-rich projects encourage students to think critically about modeling assumptions rather than focusing solely on numerical accuracy. Importantly, students from different academic backgrounds, computer science, electrical engineering, and mathematics—were able to contribute meaningfully, reinforcing the interdisciplinary nature of medical AI education.

The mixed-method assessment approach strengthened interpretation of these outcomes. CATME peer evaluations provided insight into team functioning and collaboration, while learning surveys and notebooks captured individual growth in confidence and technical understanding. Together, these instruments revealed that students not only developed technical competence, but also improved communication, documentation, and collaborative problem-solving skills—capabilities essential for modern data-driven engineering practice.

Several limitations should be acknowledged. The study involved a single cohort within one research laboratory environment, limiting generalizability. Learning gains were measured primarily through self-reported surveys, peer assessment, and artifact analysis rather than standardized concept inventories. Additionally, the rapid evolution of AI tools presents a challenge for curricular sustainability; instructors must continuously adapt examples and datasets to maintain relevance. Future work should include multi-course implementations, controlled comparisons with traditional instruction, and longitudinal tracking of student skill retention.

A further limitation concerns the alignment between the technical ambition of the selected topics and the time horizon of a single semester. Several components, particularly those involving three-dimensional reconstruction and deformable scene modeling, typically require multi-semester iteration to reach stable implementations and to support rigorous comparison across methods. In addition, the computational demands, especially for reconstruction-focused pipelines, were not consistently accessible throughout the term due to variability in hardware availability and environment stability. Consequently, students sometimes prioritized feasible baselines and incremental deliverables over full-scale optimization of computationally intensive methods, limiting the extent to which advanced reconstruction approaches could be implemented and evaluated within the same semester. Moreover, although students used heatmaps and reconstruction visualizations to assess whether outputs appeared anatomically meaningful, the project did not incorporate a formal clinician-in-the-loop review process. Without systematic expert validation, qualitative claims about clinical relevance should be interpreted cautiously, and future iterations would benefit from structured clinician feedback or annotation-based verification.

Despite these limitations, the findings suggest that medical image–centered AI projects offer a uniquely effective platform for teaching data science concepts in an engineering context. The complexity, ambiguity, and ethical considerations inherent in clinical imaging naturally promote higher order thinking and interdisciplinary integration, aligning closely with emerging workforce demands.

Conclusion

This paper presented a project-based learning framework that integrates AI-powered medical image processing into undergraduate engineering education. By engaging students with real and simulated imaging datasets and modern computer vision tools, the framework aims to bridge computation, visualization, and clinical reasoning within a unified learning experience.

Through hands-on exploration of segmentation, object detection, interpretability, and three-dimensional reconstruction, students developed a deeper understanding of how AI models interact with complex visual data. The learning process emphasized reasoning over results, encouraging students to analyze limitations, question assumptions, and reflect on uncertainty—skills essential for responsible AI deployment in healthcare and other high-stakes domains.

Early outcomes from the pilot implementation indicate increased student engagement, stronger conceptual understanding, and improved confidence in working with interdisciplinary data-driven problems. The use of authentic medical imaging data played a central role in this success by exposing students to realistic constraints that cannot be replicated through simplified classroom datasets.

As AI continues to reshape engineering practice, educational models must evolve beyond algorithm-focused instruction toward experiences that integrate data quality, interpretability, visualization, and ethical awareness. The framework presented in this work demonstrates how medical image processing can serve as a powerful educational vehicle for cultivating these competencies.

Future research will expand this approach across additional courses and institutions, refine assessment instruments, and explore how AI-supported imaging projects influence long-term student preparedness for careers in biomedical engineering, data science, and healthcare innovation. Ultimately, embedding AI-powered medical imaging within undergraduate education offers a promising pathway for preparing engineers who can reason critically, collaborate effectively, and responsibly apply AI in complex real-world systems.

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