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Application of Deep Learning in Difficult Airway Management Teaching Rounds in Anesthesiology: Transitioning from Precision Assessment to an Intelligent Instructional Paradigm

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Abstract
Difficult airway management is one of the most challenging core competencies in anesthesiology, with traditional teaching heavily reliant on experiential instruction and limited case exposure. Artificial intelligence (AI), particularly deep learning, is profoundly transforming the clinical assessment and management of difficult airways through multimodal data fusion, high-precision prediction, and intelligent assistance. This paper systematically reviews recent advancements in deep learning models for difficult airway prediction and proposes a novel framework for their deep integration into the entire workflow of anesthesiology teaching rounds. This framework facilitates a paradigm shift from 'experience-based instruction' to 'data-driven, intelligent interaction' by enabling the real-time integration of AI assessment tools during rounds, creating virtual case repositories using generative technology, constructing intelligent decision-support systems, and implementing quantitative procedural skill evaluation. This approach provides anesthesiologists with transformative tools to cultivate precise assessment capabilities, structured clinical reasoning, and proficiency in emergency decision-making.

Keywords: *Deep Learning; Difficult Airway; Anesthesia Education; Teaching Rounds; Multimodal Fusion; Artificial Intelligence.*

1. Introduction

Difficult airway management is a primary risk factor for major perioperative complications and mortality. Traditional prediction relies on bedside physical examinations such as the modified Mallampati grade, thyromental distance, and inter-incisor distance. Although valuable, these classic methods exhibit limited sensitivity and specificity. Their outcomes are susceptible to examiner experience and subjective judgment, carrying a significant risk of false negatives[1]. Within standardized anesthesiology residency training, difficult airway teaching rounds are a critical component for imparting this essential critical care skill. However, they have long faced challenges including the random and infrequent occurrence of high-quality teaching cases, difficulties in standardizing the teaching process, and the subjective nature of trainee skill assessment.

In recent years, artificial intelligence (AI), particularly deep learning, has achieved breakthroughs in medical image analysis and clinical prediction. For difficult airway assessment, studies have demonstrated that deep learning models based on facial images significantly outperform traditional clinical scoring systems in predictive efficacy [2,3]. These advancements not only provide more objective and precise decision support for clinical practice but have also injected new momentum into anesthesiology education reform. However, current research and practice predominantly focus on the clinical diagnostic assistance functions of AI. The systematic integration of AI into teaching scenarios—especially into dynamic, interactive teaching rounds—remains largely unexplored. This paper aims to address this gap by exploring the construction and application prospects of an intelligent teaching round paradigm for difficult airway management empowered by deep learning.

2. Frontiers of Deep Learning in Difficult Airway Assessment

Deep learning models can autonomously learn complex features and patterns from large datasets. Their application in difficult airway assessment has evolved from single-modal image analysis to an advanced stage of multimodal information fusion.

2.1 From Single-Modal Image Analysis to Multimodal Fusion

Early research focused on using convolutional neural networks (CNNs) to analyze frontal facial photographs for predicting difficult airways, demonstrating performance superior to traditional methods[4]. To obtain more comprehensive anatomical information, multi-view (frontal, lateral, and mouth-open) facial image analysis has become standard practice [5]. The latest research has further transcended the limitations of static images by integrating multiple data sources. For instance, the Voice-Assisted Multimodal Fusion Network (VAMF-Net) innovatively combines facial tri-view images with patient speech data. This design is grounded in the physiological insight that vocal characteristics reflect dynamic functional information, such as vocal cord mobility and airway patency, which cannot be captured by static images. Utilizing a cross-attention mechanism that prioritizes image features while incorporating speech features, VAMF-Net achieved high performance with an AUC of 0.917 and a sensitivity of 0.931 on a dataset of 1,106 cases[5]. Another study proposed the Reliable Multi-modal Prototypical Contrastive Learning Network (RMP-Net), which integrates facial images and facial anatomical keypoint coordinate maps—processed via graph convolutional networks (GCNs) to capture spatial structural relationships. It further introduces laryngoscopic image features as "prototypes" during training. Through contrastive learning, the model enhances its representation of complex anatomical structures, thereby significantly improving prediction accuracy [6].

2.2 Clinical Implementation and Systematic Application

This technology is rapidly transitioning into clinical tools. Leading medical centers have developed AI systems that integrate preliminary difficult airway assessment. For example, the "Shu Wen" AI anesthesia preoperative assessment system, developed by Tongji Hospital of Huazhong University of Science and Technology and based on large language models, interacts with patients via natural language dialogue. While completing health information collection and risk disclosure, it performs a preliminary difficult airway assessment and generates a summary for physician review. Clinical validation reported a 97.5% accuracy rate for these summaries, earning recognition from nearly 90% of anesthesiologists[7,8] . This signifies that AI assessment tools have reached a level of reliability and practicality suitable for integration into clinical workflows and teaching scenarios.

3. Empowering Teaching Rounds with Deep Learning: Establishing a New Smart Teaching Paradigm

Building on these advanced technologies, we propose deeply integrating deep learning into four core stages of difficult airway teaching rounds to construct a progressive, intelligent teaching paradigm.

3.1 Stage 1: Intelligent Pre-screening and Precise Case Selection

Prior to rounds, the teaching platform can interface with the hospital information system to perform automated, batch AI pre-screening on patients scheduled for surgery. Utilizing an assessment module integrating algorithms like VAMF-Net or RMP-Net, the system analyzes standardized facial photographs from electronic health records (and voice recordings if necessary). It outputs a difficult airway risk probability (e.g., high, medium, low) and provides key visual evidence, such as heatmaps highlighting features like retrognathia or macroglossia [6]. Based on this, the supervising instructor can efficiently identify the most pedagogically valuable suspected difficult airway cases from a large routine caseload, ensuring optimal allocation of teaching resources [9]. Concurrently, the system can employ generative adversarial network (GAN) technology to generate numerous virtual difficult airway cases based on real anatomical features, creating a digital case library for foundational training and effectively solving the problem of scarce teaching cases.

3.2 Stage 2: Immersive Interactive Rounds and Decision-Making Training

During bedside rounds, the teaching system moves to the foreground. Via tablets or AR glasses, trainees can view the current patient's AI assessment report in real-time [10] . Teaching rounds then begin not with the instructor's questions, but with a critical discussion of the AI's conclusions: "The system issued a high-risk alert, with heatmaps indicating a narrow mandibular space. Do you agree? Please verify this using your bedside physical examination findings (e.g., the '3-3-2' rule)" [11]. This process shifts the pedagogical focus from memorizing scoring criteria to advanced clinical thinking training that involves interpreting AI evidence, cross-validating with traditional methods, and ultimately forming independent clinical judgments.

Furthermore, large language models integrated with systems like "Shu Wen" can serve as intelligent question-answering and decision-support assistants. Trainees can verbally inquire at any time: "For this potential difficult airway case complicated by rheumatoid arthritis, what is the preferred sedation regimen for awake intubation?" The system can instantly generate evidence-based answers aligned with the latest guidelines and guide trainees through decision-tree analysis. This equips each trainee with a real-time "expert consultant," significantly enhancing the knowledge density and interactive depth of the teaching round.

3.3 Stage 3: Skill Simulation and Quantitative Assessment

For high-risk patients, procedural skills training is often conducted on manikins. Future integration of research on intelligent intubation robots with deep learning-based visual recognition technology could enable high-fidelity simulation training systems. A CNN model could analyze video feeds in real time to recognize a trainee's hand movements during laryngoscopy, blade insertion depth, and glottic exposure level, providing quantitative scoring against expert benchmarks [12]. The system could deliver real-time auditory feedback (e.g., "Advance the blade 2 cm further") or generate detailed post-procedure evaluation reports (including metrics like glottic exposure time and dental compression force), enabling objective and granular skill assessment.

3.4 Stage 4: Data Review and Personalized Feedback

Upon completion of teaching rounds, all procedural data—AI prediction results, trainee assessment records, discussion highlights, and simulation operation scores—are automatically archived [13]. The teaching platform then performs data analysis to generate group and individual learning reports. For instance, the system might identify a trainee who consistently underestimates risk in cases with "obesity" characteristics and subsequently provide that trainee with personalized recommendations for targeted learning materials and tests on such cases. Instructors can also use this data to identify teaching weaknesses precisely and optimize curriculum design.

4. Comparison Between Traditional and AI-Enhanced Teaching Rounds

Traditional teaching rounds and those enhanced by deep learning differ fundamentally in their core philosophy and outcomes, representing a paradigm shift in pedagogical approach.

The traditional model relies heavily on the teaching hospital's case mix and the instructor's personal experience. Access to teaching cases is sporadic, with high-quality difficult airway instances being fortuitous rather than guaranteed. The rounding process typically begins with the instructor demonstrating bedside physical examination techniques and sharing subjective experience. Trainees' assessment practices lack standardized criteria, and knowledge expansion is limited by the instructor's immediate expertise. Feedback on procedural skills and evaluation of learning outcomes are primarily qualitative and subjective.

In contrast, AI-enhanced smart teaching rounds create a data- and intelligence-centered educational ecosystem. The starting point shifts from "random encounter" to "active targeting." Through AI pre-screening of patient databases, instructors can precisely identify suspected difficult airway cases with high instructional value. This, combined with generative virtual case repositories, fundamentally addresses teaching resource limitations. During teaching interactions, the starting point becomes the critical interpretation and validation of objective predictive reports from AI models (e.g., risk probability, visualization heatmaps). For example, trainees practice and validate the traditional '3-3-2' rule by correlating it with AI-generated heatmaps indicating a narrow mandibular space [11]. This process deliberately cultivates advanced clinical thinking skills in data interpretation, cross-validation, and independent judgment formation.

Regarding knowledge support, embedded intelligent assistants (such as the clinically validated "Shu Wen" AI system [7]) act as real-time, authoritative sources of evidence-based information, capable of instantly resolving complex queries and significantly enhancing the informational density of rounds. For skill training, computer vision-based operational quantification systems enable millimeter- and second-level precision analysis of simulated intubation, providing objective scores and specific improvement suggestions—shifting from subjective estimation to precise deficiency identification. Finally, by recording and analyzing all teaching interaction data, the system generates personalized learning reports that reveal specific knowledge or judgment blind spots (e.g., systematic risk underestimation in obese patients), enabling truly personalized, precision educational interventions. The core of this transformation elevates the teaching objective from traditional "experience and skill transfer" to cultivating the essential competencies for the intelligent era: data proficiency, human-AI collaborative decision-making, and evidence-based critical thinking.

5. Challenges and Future Prospects

Despite its promise, implementing this paradigm faces several challenges: data privacy and security, the interpretability of model decision-making processes (requiring advanced visualization techniques like Grad-CAM++ [6]), high initial technical costs, and the need for instructor training in new skills.

Looking ahead, difficult airway management education will become more deeply integrated with AI. Deep learning-based intraoperative real-time warning systems (e.g., predicting intubation difficulty by analyzing laryngoscopy video) may be incorporated into teaching debriefings. Virtual reality (VR) technology combined with multimodal perception-enabled intubation robots will create immersive, zero-risk training environments for managing critical airways. Ultimately, these advancements will cultivate a new generation of anesthesiologists who are not only skilled airway managers but also versatile professional adept at leveraging AI for precise clinical decision-making.

6. Conclusion

Deep learning technology is reshaping both the clinical practice and teaching methodologies of difficult airway management. Systematically integrating advanced multimodal AI assessment models, intelligent decision-support systems, and quantitative evaluation tools throughout the teaching round workflow can establish a novel smart teaching paradigm characterized by data-driven approaches, intelligent interaction, and precise feedback. This approach not only effectively overcomes the inherent limitations of traditional teaching but also fundamentally enhances the clinical reasoning, decision-making competence, and procedural skills of anesthesiology residents. It provides a crucial pathway for the transition of anesthesiology education into the intelligent era. Future teaching rounds will serve as a collaborative arena where the clinical wisdom of experienced anesthesiologists synergizes with the precise computational power of artificial intelligence to jointly safeguard patient airway safety.

Author Contributions

Jianwei Guo and Minmin Yi conceived the paper and drafted the manuscript; Yan Cheng developed the evaluation framework and critically reviewed the manuscript. All authors reviewed and approved the final version for publication.

Data Availability

Not applicable.

Declarations

Consent for Publication

Not applicable.

Competing Interests

On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

1. Nørskov AK, Rosenstock CV, Wetterslev J, et al. Diagnostic accuracy of anaesthesiologists' prediction of difficult airway management in daily clinical practice: a cohort study of 188 064 patients registered in the Danish Anaesthesia Database[J]. Anaesthesia, 2015, 70(3): 272-81.
2. De Rosa S, Bignami E, Bellini V, et al. The Future of Artificial Intelligence Using Images and Clinical Assessment for Difficult Airway Management[J]. Anesth Analg, 2025, 140(2): 317-325.
3. Weixiong C, Yu T, Yingjie W, et al. Advances in the application of artificial intelligence for difficult airway prediction[J]. International Journal of Anesthesiology and Resuscitation, 2025, 46(3): 312-315.
4. Wilk M, Pikiewicz W, Florczak K, et al. Use of Artificial Intelligence in Difficult Airway Assessment: The Current State of Knowledge[J]. J Clin Med, 2025, 14(5)
5. Li X, Zhang G, Ye W, et al. Voice-assisted multimodal fusion network for difficult airway assessment[J]. Signal, Image and Video Processing, 2025, 19(5): 381.
6. Li X, Peng B, Yao Y, et al. Reliable multi-modal prototypical contrastive learning for difficult airway assessment[J]. Expert Systems with Applications, 2025, 273: 126870.
7. Commission HPH. AI System "ShuWen" Helps Enhance Quality and Efficiency in Anesthesia Preoperative Visits. 2025-05-23 2025-05-23]; Available from: https://wjw.hubei.gov.cn/bmdt/mtjj/mtgz/202505/t20250523_5660862.shtml.
8. Bureau WSaTI. AI Anesthesia Preoperative Visit System "ShuWen" Released with Accuracy Rate as High as 97.5%. 2025-05-06 2025-05-06]; Available from: https://kjj.wuhan.gov.cn/xwzx_8/kjspxw/202505/t20250506_2576999.html.
9. Wu J, Yao Y, Zhang G, et al. Difficult Airway Assessment Based on Multi-View Metric

Learning[J]. Bioengineering (Basel), 2024, 11(7)
10. Estrada Alamo CE, Diatta F, Monsell SE, et al. Artificial Intelligence in Anesthetic Care: A Survey of Physician Anesthesiologists[J]. Anesth Analg, 2024, 138(5): 938-950.
11. Hendrix JM, Patel R, and Friede R, 3-3-2 Rule, in StatPearls. 2025, StatPearls Publishing Copyright © 2025, StatPearls Publishing LLC.: Treasure Island (FL) with ineligible companies. Disclosure: Roshan Patel declares no relevant financial relationships with ineligible companies. Disclosure: Rotem Friede declares no relevant financial relationships with ineligible companies.
12. Hayasaka T, Kawano K, Kurihara K, et al. Creation of an artificial intelligence model for intubation difficulty classification by deep learning (convolutional neural network) using face images: an observational study[J]. J Intensive Care, 2021, 9(1): 38.
13. Battegazzorre E, Gino B, Strada F, et al. Enhancing difficult airway management training: the role of virtual reality and adaptive learning[J]. Virtual Reality, 2025, 29(1): 22.