MEIdicAI
Expert System for Airway Management Assistance in Patients Undergoing General Anesthesia
Difficult Airway Predictor

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Abstract - Airway management remains one of the most critical aspects of anesthesia, requiring timely recognition of risks and adherence to evidence-based strategies. The DAP System is a data-driven platform designed to support anesthesiologists in detecting and managing inhalational anesthesia and airway difficulties. This project integrates artificial intelligence to analyze physiological and procedural data in real time, assisting clinicians in identifying ventilation or intubation challenges and suggesting escalation protocols when needed. By combining AI with established clinical guidelines, the system promotes safer anesthetic practice, standardized event logging, and improved patient outcomes.

Index Terms - Artificial Intelligence, Airway Management, Anesthesiology, Clinical Decision Support, Patient Safety

I. Introduction

Anesthesia is essential in modern medicine. It ensures patient comfort and safety during surgeries. Among different anesthesia techniques, inhalational anesthesia is one of the most widely used because it is easy to control and works quickly. However, detecting and monitoring the depth and effects of inhalational anesthesia accurately presents significant clinical challenges. Human interpretation can lead to mistakes due to physiological differences, time limits, and conditions in the operating room.

Recently, using Artificial Intelligence (AI) in healthcare has opened new ways to improve diagnosis and decision support. Machine learning and data-driven models have shown great promise in analyzing complex physiological signals and spotting subtle patterns that clinicians might miss [3] [4]. Using these methods for monitoring anesthesia could improve anomaly detection, optimize triage decisions, and contribute to safer surgeries.

In this study, the research proposes an AI-based expert system designed to detect and assess inhalational anesthesia. The system utilizes a knowledge-based approach that integrates clinical expertise with computational intelligence to identify the type of airway anesthesia being evaluated based on patient responses. Furthermore, it assists physicians in the decision-making process [3]. The primary objective of the study is to demonstrate that an expert system can enhance accuracy, minimize human error, and contribute to a safer and more effective administration of anesthesia.

II. General Considerations

Managing patients' airways is a core skill of our specialty and, as such, has been the subject of investment in training and development for adequate clinical performance, supported by documents that help establish standards for appropriate and safe clinical practice. Managing the airway, particularly in emergencies, is often life-saving but can occasionally result in severe and even fatal complications. In patients who, after anesthetic induction, find themselves unable to manage the apnea we have conditioned, it can be tragic. The most frequent complications associated with anesthesia reported in the "closed claim analysis"—death (26%), neurological injury (22%), or permanent brain injury (9%)—are overwhelming, and the most devastating events associated with this morbidity and mortality in anesthesia are respiratory (17%).[9]

Complications in airway management occur throughout the perioperative period: 67% at induction, 15% during surgery, 12% at extubation, and 5% during recovery from anesthesia. Although the number of deaths and brain injuries during anesthetic induction has decreased from 62% (1985–1992) to 35% (1993–1999), the same has not been true for other complications. The phases of anesthesia and the increased likelihood of death or brain injury in airway emergencies are associated with persistent attempts at tracheal intubation. This has led to the development of airway management strategies for induction, maintenance, and recovery from anesthesia to improve the safety of our patients.

III. State of the Art

This document provides an overview of the theoretical foundations and current technologies related to artificial intelligence applications in anesthesiology, with a particular focus on inhalational anesthesia detection and airway management . It explores the integration of logic programming, predicate systems, real-time physiological data analysis, and clinical decision support systems aimed at improving patient safety and triage efficiency.

Airway management is a core competence in anesthesiology and a determining factor in patient safety during anesthesia, emergency medicine, and intensive care. The **difficult airway** remains one of the leading causes of anesthesia-related morbidity and mortality, often associated with respiratory complications, hypoxemia, and brain injury [5].

The development of consensus statements and clinical algorithms aims to standardize practices, promote structured training, and reduce complications — a global trend observed in organizations such as the *Difficult Airway Society* (DAS) and the *American Society of Anesthesiologists* (ASA).

A. Related Work

B1. A Novel Expert System for the Diagnosis and Treatment of Heart Disease

This work proposed a fuzzy logic–based expert system to assist physicians in diagnosing and managing heart disease. The model integrates clinical parameters such as blood pressure, cholesterol, and ECG data through a rule-based inference engine containing over 3,800 fuzzy rules. This approach allows reasoning under uncertainty and supports automated clinical decision-making. Although applied to cardiology, the study demonstrates how expert systems can encode medical expertise to enhance diagnostic accuracy — a concept that can be adapted to anesthesiology for assessing airway difficulty and supporting intraoperative decision processes [1].

B2. Development of an expert system advisor for anaesthetic control (RESAC)

In this 1992 project, developed the RESAC system, one of the first real-time expert systems designed to assist anesthesiologists in controlling anesthetic depth. The system integrates multiple physiological signals and qualitative indicators to provide dynamic recommendations on the dosage of volatile anesthetic agents. By combining rule-based reasoning with fuzzy logic, RESAC effectively manages uncertainty in patient responses and generates interpretable feedback for clinicians during surgical procedures.

Although RESAC primarily focused on anesthetic depth control rather than airway management, its architecture laid the groundwork for knowledge-based decision support in anesthesiology. The DAP System expands on this foundation by incorporating data-driven intelligence — combining expert system logic with modern artificial intelligence techniques to interpret real-time physiological and procedural data. While RESAC demonstrated the feasibility of rule-based reasoning for intraoperative guidance, DAP introduces adaptive, AI-assisted triage and airway risk detection, aiming for a more comprehensive and predictive clinical support framework. To this day, RESAC remains a relevant milestone that illustrates the transition from static rule-based systems to modern hybrid AI approaches capable of real-time learning and decision refinement [2].

IV. Clinical Framework for Airway Management

There are two main types of airway anesthesia scenarios addressed in this discussion: the **difficult airway**, which may be either **predictable** or **unpredictable**, and situations involving challenging **laryngoscopy**. These categories play a crucial role in guiding preoperative planning, airway assessment, and the implementation of safe and effective anesthetic strategies.

A. Definition of Difficult Airway

The Portuguese consensus defines a **difficult airway** as a situation in which an experienced anesthesiologist encounters difficulties in ventilating, intubating, or maintaining adequate oxygenation using standard techniques. Recognized categories include:

- Difficult mask ventilation;
- Difficult supraglottic device placement;
- Difficult laryngoscopy;
- Difficult or failed tracheal intubation;
- Difficult cricothyrotomy.

The management approach should focus on early recognition, contingency planning, and structured, escalating intervention.

B. Airway Evaluation and Prediction of Difficulty

Airway assessment involves both clinical history and physical examination, supported by structured mnemonics such as:

- **MOANS** – predictors of difficult mask ventilation;
- **LEMON** – predictors of difficult laryngoscopy;
- **RODS** – predictors of difficult supraglottic device use;
- **SHORT** – predictors of difficult cricothyrotomy.

Although several predictive tests exist, none is entirely reliable on its own. Therefore, an integrated and contextualized assessment is essential [3] [6].

C. Management Strategies

Airway management is generally divided into two major clinical scenarios:

1) Predictable Difficult Airway:

- Consider alternative anesthetic techniques or awake intubation;
- Maintain spontaneous ventilation whenever possible;
- Ensure assistance and a defined rescue plan;
- Consider fiberoptic bronchoscopy, videolaryngoscopy, or cricothyrotomy depending on the case.

2) Unpredictable Difficult Airway:

- **Plan A:** Optimized tracheal intubation attempt (up to four attempts);
- **Plan B:** Use of supraglottic airway devices;
- **Plan C:** Maintain oxygenation and ventilation through non-invasive means;
- **Plan D:** Perform invasive access via cricothyrotomy (needle or surgical).

V. DAP Project

The DAP (Difficult Airway Predictor) project aims to develop an **expert, rule-based decision-support system** that assists anesthesiologists in the management of difficult airways. The system operates through a structured **question-and-answer reasoning process**, emulating the logic of clinical decision-making. Each interaction corresponds to a decision node from the knowledge base, and at every step, the system formulates a question based on previous responses, updating its internal state until a safe and clinically justified conclusion is reached.

The flowchart in Fig. 1 represents the program's **knowledge base** — a structured map of all rules and their logical relationships — serving as the foundation of the expert system. Unlike data-driven models, the reasoning process is entirely explainable, reproducible, and traceable to established airway management guidelines.

The methodological framework integrates five main components: label=(v)

1) Acquisition and harmonization of physiological and clinical data;
2) Preprocessing and labeling for rule condition structuring;
3) Integration of airway management logic through rule-based reasoning;
4) Interactive inference cycle based on clinician feedback;
5) Validation using simulated and retrospective case scenarios.

A. Data Acquisition

We collect time-synchronized physiological signals and metadata commonly available in the operating room, as well as patient-reported data. These include:

- **Physiological signals:** e.g., SpO_2, $EtCO_2$, heart rate;
- **Procedural/clinical variables:** predictors for difficult airway (*LEMON, MOANS, RODS, SHORT*), airway device used, number of attempts, operator experience, and outcome labels.

B. Clinical-Knowledge Integration

Clinical airway management logic is encoded into a rule set that mirrors established guidelines (e.g., national anesthesia societies). The system employs mnemonic frameworks such as *LEMON*, *MOANS*, *RODS*, and *SHORT* to classify predicted difficulty levels. Each rule acts as a safety checkpoint that ensures traceable, guideline-compliant recommendations — for example, escalation to supraglottic devices, maintenance of spontaneous ventilation, or invasive airway access when indicated.

C. Decision Engine and Workflow

The inference engine follows a **question-driven, rule-based workflow**. Each node in the flowchart corresponds to a rule (or set of rules) from the knowledge base. At runtime, the engine maintains a working memory that stores the clinician's answers. Rules continuously evaluate this context and *fire* when their conditions are satisfied, determining the next question or triggering a final recommendation.

a) Operational logic.:

- **Ask → Answer → Update:** The system asks a targeted question; the user's response updates the working memory.
- **Rule firing:** Guard conditions (e.g., predictors from *LEMON, MOANS, RODS, SHORT*, number of attempts, device in use) activate the appropriate rule(s).
- **Next step or conclusion:** The fired rule defines the next question or emits a final clinical action (e.g., switch to supraglottic device, maintain spontaneous ventilation, proceed to invasive access).

b) Safety and traceability.: Safety constraints are **embedded within the rules themselves** — including limits on attempts, escalation criteria, and mandatory checks for oxygenation. Every decision is explainable, as each transition in the reasoning chain is directly linked to the specific rule that fired.

c) Scope.: No machine-learning component participates in the real-time inference loop. Any statistical analysis or AI model is limited to *offline* validation and refinement of the rule set; it does not override or interfere with the rule-based execution.

D. Validation Protocol

The validation process adopts a one-stage evaluation:

- **Retrospective cross-validation:** Data are split according to patient characteristics satisfying *LEMON*, *MOANS*, *RODS*, or *SHORT* predictors;
- All system recommendations are compared against expert clinical decisions, which serve as the reference standard.

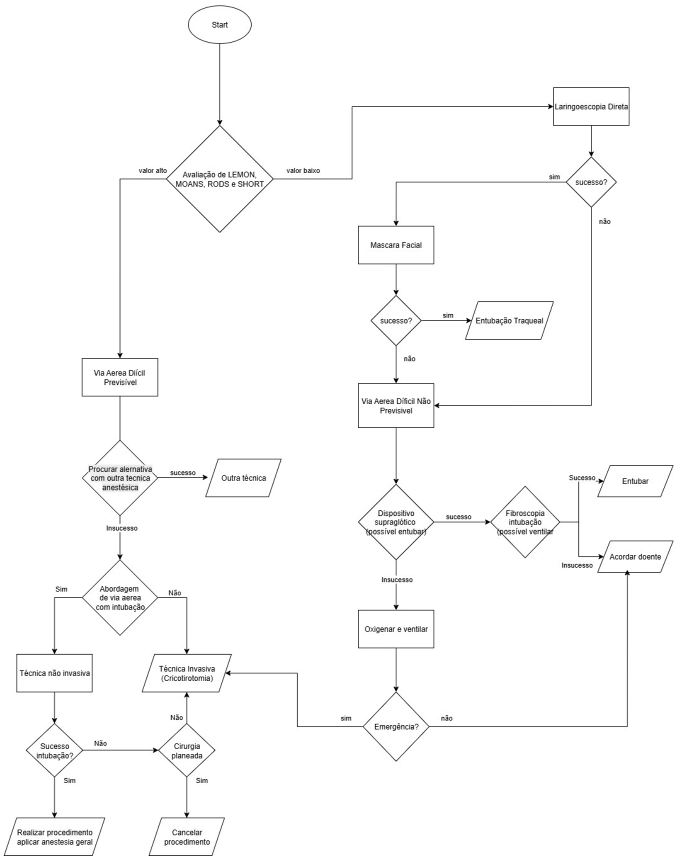

Fig. 1. DAP System decision flowchart for difficult airway management used to derive the system's rule base and logic.

VI. Impact Discussion

The growing adoption of artificial intelligence in healthcare represents a major shift in how clinical information is interpreted and applied to improve patient outcomes. Within anesthesiology, intelligent systems such as DAP have the potential to redefine safety standards, streamline workflows, and enhance the precision of intraoperative monitoring.

By integrating computational intelligence into anesthetic practice, the DAP System demonstrates how technology can complement human expertise rather than replace it. Its approach promotes faster recognition of critical events, supports informed clinical decisions, and reduces the risk of human error during complex procedures. Beyond immediate clinical benefits, such systems also contribute to long-term improvements in research by generating structured data and standardized decision logs.

In general, the impact of DAP extends beyond operating rooms. It encourages a cultural shift toward data-driven medicine, where continuous learning and real-time analytics enhance clinical performance and accountability. Moreover, by incorporating explainable AI methods, the system strengthens transparency and trust between technology and medical professionals — a crucial factor for widespread clinical adoption. Ultimately, DAP exemplifies the transformative potential of artificial intelligence in healthcare, paving the way for more adaptive and simple medical practice.

VII. Conclusion and Future Directions

The DAP System represents a significant step forward in integrating artificial intelligence with clinical expertise to enhance airway management and patient safety during anesthesia. By combining rule-based expert systems with machine learning algorithms, the platform demonstrates how technology can support—rather than replace—clinical decision-making in the operating room. The hybrid approach ensures that AI recommendations are always grounded in established clinical guidelines while benefiting from the pattern-recognition capabilities of modern computational methods.

The results of this work underscore the importance of explainable AI in healthcare environments, where transparency and clinical trust are paramount. By encoding the LEMON, MOANS, RODS, and SHORT mnemonics into a structured knowledge base, the MEIdical System provides clinicians with interpretable recommendations that align with consensus-based practice standards. This alignment is critical for clinical adoption and long-term integration into perioperative workflows [7].

In conclusion, the DAP System exemplifies the transformative potential of AI in anesthesiology. As technology continues to evolve, intelligent clinical decision support systems will play an increasingly important role in reducing human error, improving patient outcomes, and advancing the field toward more personalized and data-driven anesthetic practice.

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