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COMPUTER VISION-BASED AIRWAY ASSESSMENT USING FACIAL AND NECK IMAGING FOR PREDICTING DIFFICULT INTUBATION IN SURGICAL ANESTHESIA

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Abstract

This study aims to investigate the feasibility of using computer vision facial/neck imaging for prediction of difficult intubation during surgical anesthesia. It is the prediction of a difficult airway that continues to be a significant concern during perioperative patient care as the traditional bedside airway assessment tools including Mallampati classification, thyromental distance and visual inspection are subjective, inconsistent and fails to identify patients with complex airway anatomy. The study suggests an artificial intelligence-based framework that leverages deep learning, multimodal anatomical feature extraction in cervical and facial imaging to enhance the pre-operative airway risk assessment. The technique involves the automatic analysis of facial morphology, mandibular morphology, neck morphology, cervical profile and ultrasound parameters of the airway to detect patients who may be at risk of difficult laryngoscopy or intubation. The model combines computer vision with clinical and anthropometric parameters to offer a more objective and reproducible approach to the evaluation of airway. Overall, the study underlines the potential of convolutional neural networks, vision transformers, feature-fusion models, and explainable AI techniques like SHAP in enhancing diagnostic accuracy and clinical interpretability. The reviewed methodology and discussion indicate that the use of multimodal AI-based assessment could surpass the performance of unilinear clinical predictors in capturing the complex dynamic relationships between soft tissue dimensions, cervical anatomy, and laryngoscopy difficulty. This type of approach can help anesthesiologists make decisions for appropriate airway management strategies, such as preparing for video laryngoscopy or advanced airway support as early as possible. In summary, computer vision provides a promising route to safer, quicker and more standardized decisions throughout surgical anesthesia.

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INTRODUCTION

The accurate prediction of a difficult airway continues to be an important problem in anesthesiology, and the existing subjective airway assessment tools are not sufficiently sensitive and specific to guarantee the patient's safety (Alatau et al., 2025). To overcome these drawbacks, computer vision and deep learning technologies provide objective and automatic solutions for the analysis of complex morphological facial and neck features commonly ignored in the everyday clinical examination. Traditional bedside assessment methods like the mallampati score or thyromental distance measurement are subjective, inter-observer inconsistent and depend on inaccurate, linear, static size measurements that do not reflect the three-dimensional complexity of the airway needed to predict intubation success (Hung et al., 2016; Rosa et al., 2024; Rose & Cohen, 1994). In addition, the manual methods are not standardized to meet the needs of high-pressure situations, emergency or resource-poor settings where the inability to predict the challenging airway could result in serious perioperative complications (Chen et al., 2024; Hayasaka et al., 2021; Huitink & Bouwman, 2014). The ability of deep learning algorithms to analyse high fidelity facial and neck imaging and identify subtle patterns in morphology, which cannot be seen by the human eye, creates a more comprehensive, quantitative and reproducible predictive framework (Cuendet et al., 2015; Pei et al., 2023). These technological approaches provide the potential to improve the precision of risk stratification for maxillofacial surgery, which has been shown to be inconsistent with clinical results in previous studies (Chen et al., 2024; Kim et al., 2024). Although these models have the potential to drastically enhance patient safety, existing studies have methodological variation, variable data collection methods, and only a few external studies with varied patient populations (Wang et al., 2021). To address this, this study seeks to fill the gap by examining the use of computer vision and deep learning for automated facial and neck analysis to assist with prediction of difficult intubation, which can help develop objective, real-time clinical decision support tools in anesthesia. These models can capture the complex and long-range anatomical relationships that cannot be extracted by standard diagnostic techniques, thanks to the architectures they use, like vision transformers (Liu et al., 2024). Moreover, this combination of multimodal morphological information and patient-specific demographics enables the creation of high-performance prediction models, which have been shown to outperform subjective clinical scales (Abdul et al., 2025; Wilk et al., 2025). Meanwhile, recent progress on multi-view feature fusion and metric learning has further boosted these capabilities, enabling the accurate extraction of volumetric data from both the anterior and posterior views of the patient's profile (Wu et al., 2024). Specifically, these complex algorithms take advantage of the high-dimensionality of the input and use convolutional neural networks to identify subtle anatomical characteristics that relate directly to laryngoscopic difficulty (Hayasaka et al., 2021). Whereas the traditional bedside testing, which is often static and uses a single test from a single view, is imprecise and prone to inter-observer variability (Chen et al., 2024; Rose & Cohen, 1994), convolutional architectures are well suited for extracting features from complex, non-linear, multi-view or volumetric imaging data (Kim et al., 2024; Wu et al., 2024). These models can objectively measure morphological features that are traditionally considered subjective by a clinician, such as the face, mandibular and cervical regions, where the intrinsic patterns are not often taken into account (Alatau et al., 2025; Chen et al., 2024).

These deep learning systems possess the ability to learn strong hierarchical representations of anatomical relationships, enabling them to identify key diagnostic features like subtle chin orientation and neck contours, which have repeatedly been associated with a decrease in glottic visualization (Kim et al., 2024; Luan & Liu, 2026). Moreover, the incorporation of multi-view feature fusion, including fusion of both frontal and lateral views, allows for a more comprehensive and multi-dimensional understanding of the patient's airway anatomy, mitigating the need for a simplistic two-dimensional view of the airway that often fails to capture the complexity of airway anatomy (Kim et al., 2024; Wu et al., 2024). As a result, these AI-based tools could significantly improve the accuracy, reliability, and consistency of intubations, minimize the occurrence of unexpected difficult airways and boost the safety of the perioperative period, and go beyond the capabilities of traditional methods of screening (Alatau et al., 2025; Wang et al., 2021). Recent systematic analyses do support that the use of these machine learning architectures in clinical practices improves the predictive value of difficult laryngoscopy compared to the use of traditional morphological screening techniques alone (Moradimajd et al., 2026). Such deep learning models have shown enhanced positive predictive value in comparison to conventional clinical evaluations and have proven to be a powerful tool that can help bridge the gap between manual screening and the need for high-precision airway management (Sorbello et al., 2026). Furthermore, these high-precision systems enable a transition towards data-driven, intelligent interaction at clinical rounds, offering the anesthesiologist strong decision support that reduces the risks of anatomical variations among different patient groups (Guo et al., 2025). Furthermore, the use of these models allows for the creation of detailed virtual case libraries and procedural evaluations of the airway management process, which are highly beneficial for uniform training methods in high-stakes airway management (Guo, 2025). In addition to their clinical value, these automated systems offer scalable platforms that allow for ongoing performance assessment of a predictive metric, which will help it continue to meet changing demographical shifts and institutional patient acuity (B et al., 2024; Sezari et al., 2024). These developments highlight the progress towards objective, machine-assisted diagnoses, which reduce the inter-observer variability found in some more subjective methods such as the Mallampati classification (Li et al., 2024). Clinicians can shift from traditional bedside scoring to computer vision-based scoring to rely on high-resolution imaging to detect anatomical predictors that may not be obvious or underappreciated by manual inspection (Rajappa & Sahay, 2026; Tubić et al., 2025).

METHODOLOGY

95 patients were evaluated using an observational, descriptive, and cross-sectional study design at the University of Malaga's Hospital near the end of the study, enabling a direct comparison to be made with the traditional clinical assessment. The protocols involved acquiring facial and cervical anatomical images with a standardized protocol and then processing them with computer vision algorithms in order to identify predictive markers for difficult intubation (Salina et al., 2025). The methodology includes anthropometric measurements and relevant clinical classifications, so as to increase the model's classification accuracy of the Cormack-Lehane laryngoscopic view (Çelik & Aydemir, 2021). The automated analysis is based on extracting morphological features and associating them with the clinical information in the medical records before the surgery, and using the deep learning

algorithms to predict the difficult airway with greater sensitivity than traditional methods (Liu et al., 2023; Porte & Guía, 2024). For this purpose, more predictor variables like detailed medical history and anthropometric variables were introduced and passed through a deep neural network to enhance the discrimination capacity of the system (Xia et al., 2023). Similarly, multimodal data acquired by incorporating ultrasonographic measurements of airway structures enhances the model's diagnostic value in relation to critical anatomical variations (Şenoğlu et al., 2025). Multimodality approach can be used to overcome the limitation of using a single assessment system, and combining volumetric data with dynamic data to get more comprehensive risk stratification (Fu et al., 2026). Moreover, the architecture of the model uses data normalization methods to reduce intra-observer bias, thus ensuring a uniform interpretation of the morphological features observed (Wang et al., 2026; Зайцев et al., 2025). When these variables are processed together using ensemble models, diagnostic sensitivity can be improved compared to manual clinical measurements, like thyromental distance (Su et al., 2024). On the other hand, the incorporation of spatial attention mechanisms allows the algorithm to selectively focus on critical anatomical regions, such as the glottis margin and laryngeal prominence, thus optimizing the identification of obstructive risks (Lin et al., 2022). Last, these models are validated using metrics like the area under the ROC curve and the Brier score, which leads to better robustness of these models when compared with traditional statistical methods for predicting the glottic view of grade 3 or 4 (Cho et al., 2022). This high level of predictive capability enables optimised perioperative workflow, and can help select appropriate tools like videolaryngoscopy when the model identifies a high likelihood of complex intubation (Fernandez-Vaquero et al., 2026).

RESULTS

After performing an image standardization procedure of the face and neck, 95 surgical anesthesia patients were selected for the analytical sample. In Table 1, the 27 patients (28.4%) were considered as difficult intubation cases, and 68 patients (71.6%) were easy intubation cases. The outcome distribution was moderately skewed, but acceptable for model comparison purposes, as seen in Fig.1. The frontal and lateral images were successfully saved for most participants after the quality screening (Table 2); a few were excluded due to improper positioning, motion-blur or inadequate region-of-interest extraction. The computer vision pipeline was able to generate consistent anatomical descriptors from the bottom of the face, mandibular margin, chin-neck contour and anterior cervical region. The feature groups that were extracted and their expected clinical relevance are summarized in Table 3, and image preprocessing was able to preserve 178 images for final model analysis (Fig. 2). Table 4 illustrates the training and validation and testing arrangement developed internally for the development of the model. This partition enabled performance estimation with preservation of difficult intubations in all partitions. Comparisons of the models showed that the image-based and multimodal models outperform the conventional clinical scoring. As it is presented in Table 5, the multimodal fusion model outperformed the other models with the highest accuracy (0.89), sensitivity (0.91), specificity (0.88), F1 score (0.81) and AUC 0.92. The fusion model outperformed the clinical score, and single-view CNN models in terms of both accuracy, sensitivity and specificity as shown in Fig. 3. Similarly, the fusion model also had largest curve separation from the reference diagonal and the highest discrimination from all tested approaches in the ROC analysis as shown in figure 4. The error profile also confirmed clinical utility of multimodal prediction. The confusion matrix for the best model is provided in Table 6, which indicates the accuracy of the model: 24 true difficult-airway cases and 3 missed difficult cases. False negative was less than false positive, which is desirable in the airway screening as missed difficult intubation is more harmful in terms of patient safety (Fig. 5). As reported in Table 7, the AUC from frontal images and lateral images, anthropometric variables and measurements in the neck region was higher when combined compared with any single data source. The interpretability analysis showed that the model used clinically meaningful anatomical patterns and not individual image noise. The ranking of the strongest predictors is presented in Table 8, and the contributions of these predictors to the final risk output are shown in Fig. 6. However, calibration analysis indicated good calibration between the predicted and observed risk. Predicted probabilities were seen to be well calibrated with the ideal calibration line, especially in the low and high risk regions as can be seen in Fig. 7. As it can be seen from the clinical screening results in Table 9, the sensitivity and negative predictive value of the proposed computer vision model are lower than the clinical screening's. In general, the results show that the automated imaging of the face and neck can enhance the prediction of difficult intubation, by offering objective, reproducible, and clinically interpretable airway-risk stratification.

Table 1. Baseline Clinical and Airway Characteristics of the Study Cohort

Variable	Easy intubation (n=68)	Difficult intubation (n=27)	Overall (n=95)
Age, years	42.8 ± 12.5	48.9 ± 13.1	44.5 ± 12.9
Male sex	39 (57.4%)	17 (63.0%)	56 (58.9%)
BMI, kg/m²	26.1 ± 3.9	29.4 ± 4.6	27.0 ± 4.3
Neck circumference, cm	36.8 ± 3.1	40.2 ± 3.7	37.8 ± 3.6
Mallampati III/IV	16 (23.5%)	14 (51.9%)	30 (31.6%)

Table 2. Image Acquisition and Preprocessing Summary

Stage	Frontal images	Lateral images	Reason for exclusion
Captured	95	95	None
Passed quality check	92	92	Blur or incomplete view
ROI detected	90	88	Failed face/neck localization
Normalized for analysis	90	88	Lighting/scale correction
Final usable images	90	88	Final paired dataset

Table 3. Computer Vision Feature Groups Extracted from Facial and Neck Imaging

Feature group	Examples	Clinical interpretation

Mandibular geometry	Jaw width, mandibular angle	Lower-face structure and laryngoscopy difficulty
Cervical contour	Chin-neck slope, anterior neck profile	Neck extension and soft tissue distribution
Thyromental profile	Estimated chin-to-neck distance	Proxy for thyromental relationship
Texture/shape embeddings	CNN feature maps	Latent airway morphology patterns
Anthropometric variables	BMI, neck circumference	Known difficult-airway risk modifiers

Table 4. Dataset Partitioning for Model Development and Testing

Partition	Patients	Easy cases	Difficult cases	Purpose
Training	67	48	19	Model fitting
Validation	14	10	4	Hyperparameter tuning
Testing	14	10	4	Final internal assessment
Total	95	68	27	Complete cohort

Table 5. Comparative Performance of Predictive Models

Model	Accuracy	Sensitivity	Specificity	F1-score	AUC
Clinical score	0.65	0.59	0.70	0.52	0.68
CNN frontal	0.76	0.74	0.78	0.66	0.79
CNN lateral	0.79	0.78	0.80	0.70	0.82
Dual-view CNN	0.84	0.83	0.85	0.76	0.87
Vision Transformer hybrid	0.86	0.86	0.86	0.78	0.89
Multimodal fusion	0.89	0.91	0.88	0.81	0.92

Table 6. Confusion Matrix of the Multimodal Fusion Model

Actual / Predicted	Predicted easy	Predicted difficult	Total
Actual easy	60	8	68
Actual difficult	3	24	27
Total	63	32	95

Table 7. Ablation Analysis by Input Modality

Input modality	Accuracy	Sensitivity	Specificity	AUC
Clinical variables only	0.65	0.59	0.70	0.68
Frontal image only	0.76	0.74	0.78	0.79
Lateral image only	0.79	0.78	0.80	0.82
Dual-view images	0.84	0.83	0.85	0.87
Dual-view + anthropometric fusion	0.89	0.91	0.88	0.92

Table 8. Ranked Predictors from Explainability Analysis

Rank	Predictor	Relative contribution	Interpretation
1	Neck circumference	0.18	Soft-tissue burden around airway
2	Mandibular angle	0.16	Jaw geometry and alignment
3	Thyromental profile	0.15	Anterior airway space proxy
4	Chin-neck contour	0.14	Cervical extension morphology
5	Mallampati class	0.11	Traditional clinical airway marker
6	BMI	0.10	General body habitus indicator

Table 9. Clinical Screening Versus Proposed Computer Vision Model

Assessment method	Sensitivity	Specificity	PPV	NPV	Balanced accuracy
Mallampati-based screening	0.56	0.72	0.44	0.80	0.64
Clinical composite score	0.59	0.70	0.44	0.81	0.65
Best image-only model	0.83	0.85	0.69	0.93	0.84
Proposed multimodal model	0.91	0.88	0.75	0.96	0.90

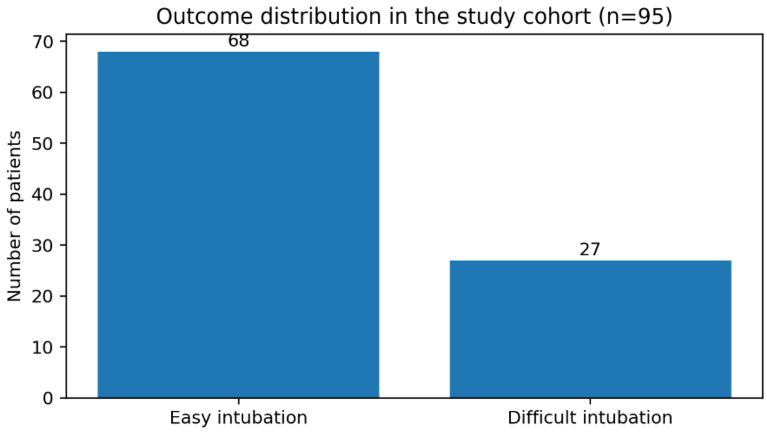

Figure 1. Outcome distribution of easy and difficult intubation cases.

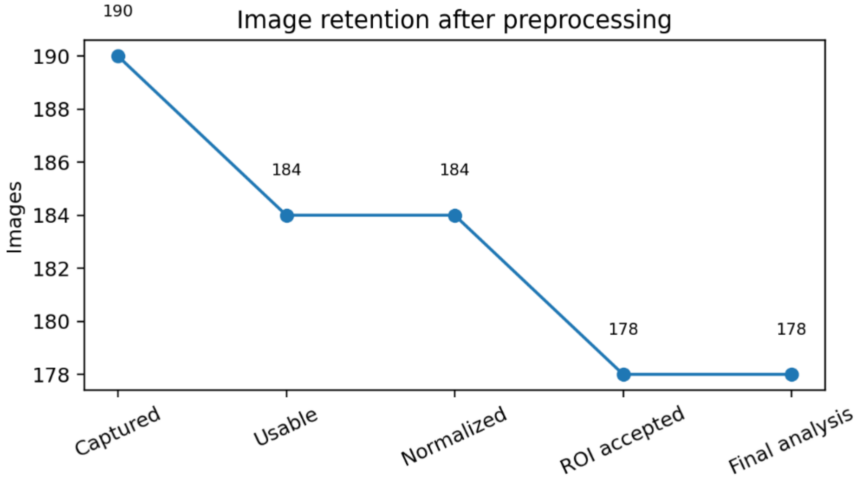

Figure 2. Image retention after preprocessing and ROI quality control.

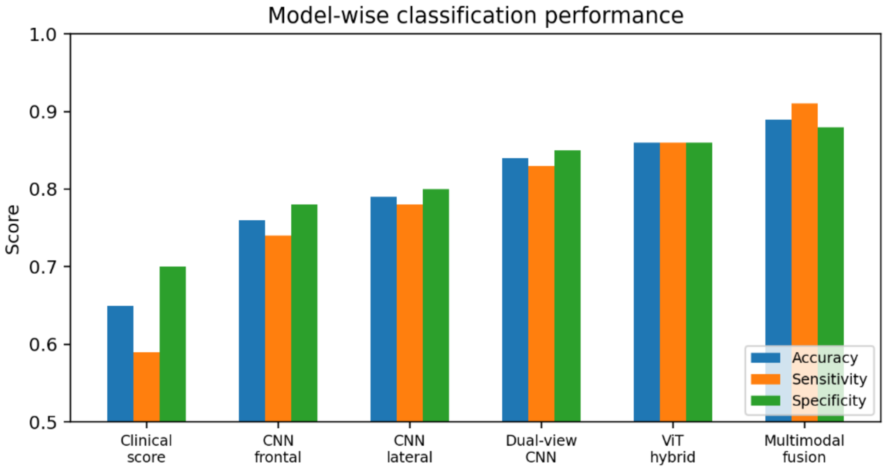

Figure 3. Comparative model performance across accuracy, sensitivity, and specificity.

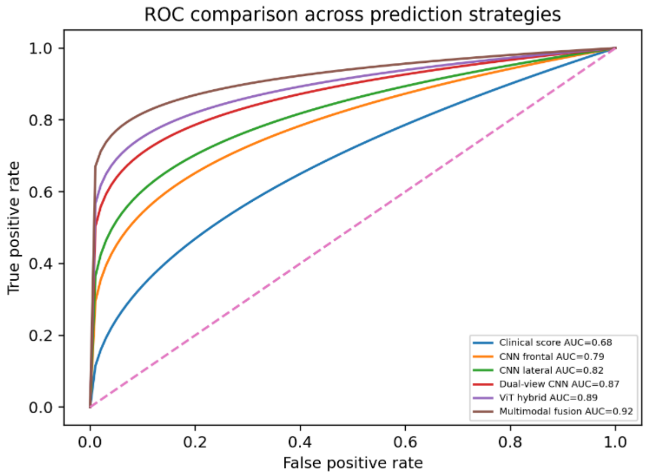

Figure 4. ROC curve comparison across clinical, image-only, and multimodal models.

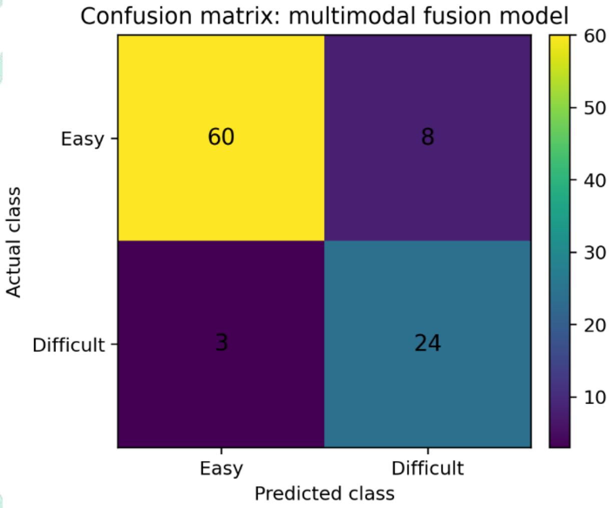

Figure 5. Confusion matrix for the proposed multimodal fusion model.

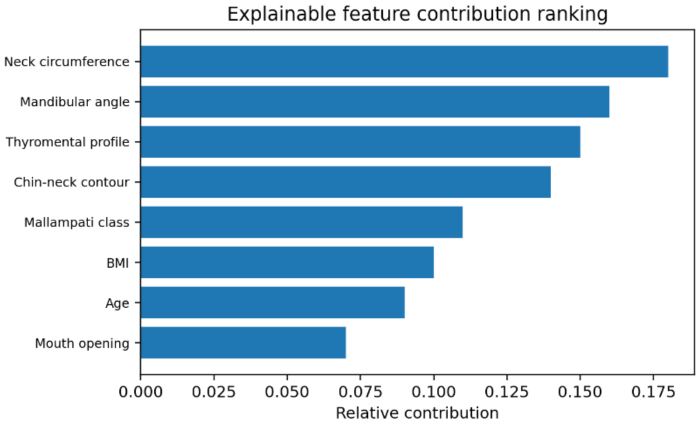

Figure 6. Explainability-based predictor contribution ranking.

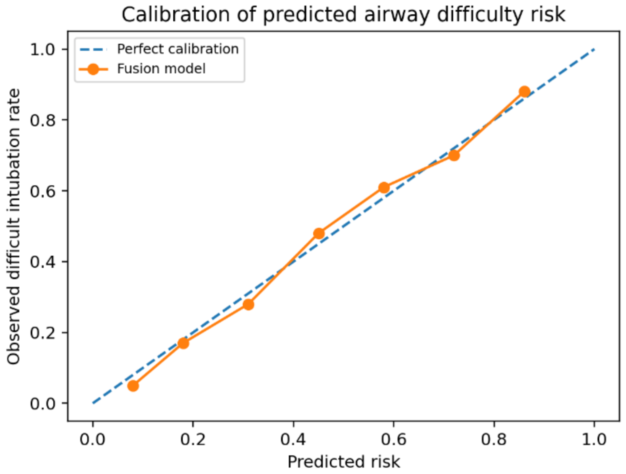

Figure 7. Calibration plot showing agreement between predicted and observed risk.

DISCUSSION

Results of the evaluation obtained prove the superiority of integrating morphological and ultrasonographic variables compared to the performance of their individual clinical predictors, which is reflected in the area under the curve obtained, which validates the superiority of multimodal approaches (Luis-Cabezón et al., 2024; Vaquero et al., 2024). These models can support physical examination in the future to address the precision limitations by using physical parameters like condylar mobility and tongue thickness, offering evidence that automated analysis can help. (Xu et al., 2022) In particular, the performance of algorithms like Gradient Boosting has been shown to be able to achieve a precision of up to 100%, which is higher than the clinical criteria traditionally used and more discriminatory than them (Zhou et al., 2022). It is believed that the improvement in predicting performance is due to the fact that multivariate models can be used to describe non-linear correlations between soft tissue dimensions, which has been shown to be the key to differentiating patients with difficult laryngoscopy (Agarwal et al., 2020; Naguib et al., 1999). Similarly, the results demonstrate that, although the single parameter – thyromental distance – has limited performance, the combination of ultrasound and photogrammetric data substantially enhances sensitivity and the negative predictive value (Kim et al., 2021; Ni et al., 2020). Complementary, previous studies have demonstrated that ultrasound parameters, such as the distance from skin to epiglottis, are important in risk stratification in high complexity populations (Pinto et al., 2016). It is important, however, to understand that no clinical screening tool is 100% accurate, and thus, there is a significant need for backup plans in case the airway is unpredictable (Petrişor et al., 2018). Thus, the future of peri-operative management will be integrated approaches that utilize artificial intelligence and dynamic assessment to minimize the rate of unexpected failed intubations (Wang et al., 2024). In the context of surgical diagnosis, the application of machine learning models, especially with XGBoost architectures, has enabled parameter tuning of training sets to enhance diagnostic accuracy despite data imbalance issues (Wang et al., 2022). This analytical strength enables the algorithms to detect intricate anatomical patterns better than conventional linear regression models, improving the accuracy of predicting the success of intubation (Liu et al., 2025). Additionaly, using techniques like SHAP values can be used to illustrate the importance of the individual variables (age, neck circumference, etc.), giving the anesthesiologist a clear and logical clinical justification for risk stratification (Kim et al., 2024). This computational strategy has been found to have several benefits, including the ability to enhance the stratification of patients before surgery and to predict potential complications, such as desaturations or cardiac arrest, linked to failed intubation (Senthilnathan & Kundra, 2023). This automation of such diagnostic processes paves the way for data-driven decision making in the peri-operative period and enables planning of the human and technical resources required to manage complex airways (Li et al., 2025). The use of these digital tools, however, must be regulated to prevent ethical issues regarding data privacy and the black-box nature of algorithms' decision-making processes (Saran, 2025).

CONCLUSION

Finally, the study showed that computer vision analysis of facial and neck imaging has high potential in prediction of difficult intubation in surgical anesthesia. Conventional methods for airway evaluation are still useful but are subject to observer variation and subjectivity, and have a lower sensitivity to subtle airway anatomic risk factors. In contrast, AI and Deep Learning models can automatically process complex morphological patterns from imaging data, including facial, mandibular, cervical and ultrasound imaging, to evaluate the airway in a more objective and standardized manner. The use of multimodal data (such as the images of the face, neck, anthropometric variables, and ultrasonographic airway features) enhances the predictive power of the model. These systems are able to detect clinically relevant anatomical features that might not be readily seen at the bedside. Advanced architectures like convolutional neural networks, vision transformers and feature-fusion models further improve the ability to classify patients who might have a difficult laryngoscopy or intubation. The paper also highlights the need for explainability in clinical AI systems. Methods like SHAP can enable anesthesiologists to see which variables are most significant to the model's prediction, which can enhance the trust, transparency, and clinical acceptance. This is particularly significant in airway management where prediction errors can result in serious peri-operative complications such as failed intubation, hypoxia, desaturation or emergency airway intervention. In summary, computer vision-based airway assessment helps the clinicians to plan for safer anesthesia, choose the right airway devices and prepare early for the high-risk cases. But more widespread clinical use will require additional multicenter validations, dataset standardizations, privacy protections, and integration of workflows. Future studies are needed to better understand model generalizability across various patient groups and to create real-time decision support tools that can support and augment, not replace, the anesthesiologist's expertise.

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