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Voice Analysis as a Method for Preoperatively Predicting a Difficult Airway Based on Machine Learning Algorithms: Original Research Report

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ABSTRACT

Background and Aims: An unanticipated difficult airway is one of the greatest challenges for anesthesiologists. Proper preoperative airway assessment is crucial to reducing complications. However, current screening tests based on anthropometric features are of uncertain benefit. Therefore, our study explores using voice analysis with machine learning algorithms to predict a difficult airway.

Methods: Observational, multicenter study with N = 438 patients initially enrolled at Centro Medico Teknon and Institut Universitari Dexeus (2019–2022) for the research study. After excluding 125 patients, N = 313 were included. Ethics committee approval was obtained. Adults ASA I-III scheduled for elective procedures under general anesthesia with endotracheal intubation were selected. Patient clinical features and traditional predictive tests were collected. Vowels "A, E, I, O, U" were recorded in normal, flexion, and extension positions. Cormack grade was assessed, and data were analyzed using KNIME, resulting in multiple models based on demographics and voice data. ROC curves and other metrics were evaluated for each model.

Results: Among multiple models evaluated, two yielded the best performance to predict a difficult airway both exclusively analyzing Cormack I and IV cases which showed the most distinct differences. The variables included in each model were the following: Model 1; included demographic data, vowel "A" in all positions and harmonics of the voice achieving an AUC of 0.91. Model 2; Included demographic data, vowel "O" in normal positions and voice parameters (Shimmer, Jitter, HNR); achieving in an AUC of 0.90. In contrast, models which focused on analyzing all Cormack grades (I, II, III, IV) cases performed less effectively.

Conclusions: Acoustic parameters of the voice together with the demographic data of the patients, when introduced into classification algorithms based on machine learning showed promising signs of predicting a difficult airway.

1 | Introduction

The occurrence of an unanticipated difficult airway is one of the greatest challenges faced by anesthesiologists with studies reporting an incidence rate of 1.5%–13.5% [1]. The American Society of Anesthesiologists (ASA) defines a difficult airway as a situation where a trained anesthesiologist encounters difficulty with facemask ventilation, tracheal intubation, extubation, or invasive airway procedures [2]. An unexpected difficult airway is a life-threatening situation that significantly contributes to anesthesia-related morbidity and mortality [3]. A closed claim analysis carried out by M. Joffe et al. analyzed claims with difficult tracheal intubation as the primary damaging event [3]. Their findings showed that despite updated guidelines and improved techniques, preventable complications in tracheal intubation still occur, often due to inadequate preoperative assessment, failure to anticipate, and situation unawareness [3]. In detail, inadequate preoperative airway evaluation contributed to 17% of claims related to major complications from a difficult airway [4]. Moreover, Crosby et al [5], collected anesthesia airway-related claims and showed that in 59% of them, there was an inadequate or incomplete preoperative airway examination. The modified Mallampati test, widely used preoperatively as screening for a difficult airway, was developed by S.R. Mallampati in 1983 [6] and modified by Samson and Young later on [7]. Roth et al., [8] carried out a large systematic review in 2018 in which the Modified Mallampati test obtained a mean sensitivity of 0.53% [0.47–0.59] (CI 95%) for difficult intubation, showing that the performance of this score ranges from poor to good and is characterized by significant variability and high heterogeneity among studies [9]. Predicting a difficult airway is most effective using a multivariate index that combines several predictors, as this approach improves sensitivity and specificity compared to individual tests [10, 11]. One of the most used tests is the Arne test which is based on a multivariable index with a cut-off value of 11 for predicting a difficult intubation [12]. The diagnostic accuracy and feasibility of these tests are questionable because unpredicted difficult intubations remain high despite its routine use. Norkov et al., in 2015 revealed that only half of the difficult intubations were predicted [13]. For this reason, new methods like ultrasound, functional MRI, and CT scans have been proposed to improve airway assessment [14–17]. Artificial intelligence has increasingly supported new methods for predicting intubation difficulty, with several studies developing AI models that use facial images for this purpose [18, 19]. In 2021, Tatsuya et al. developed an AI model to classify difficult intubation using 16 images per patient from 205 participants, yielding promising results [20]. In recent years, voice has emerged as a new potential method for the detection of a difficult airway, building on the fact that voice parameters can reflect the anatomical characteristics of the upper airway [21–24]. Carvalho et al, in 2021 already showed a significant association between three formants and Cormack-Lehane scale classification in a study including 453 participants [22]. Our study explores using machine learning algorithms to analyze voice characteristics for predicting a difficult airway, aiming to improve preoperative assessment and enhance airway management safety.

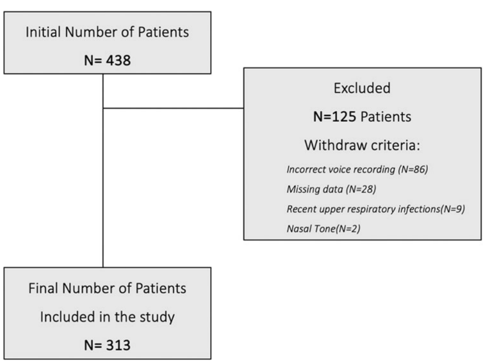

FIGURE 1 | Flowchart of the patient selection process.

2 | Methods

2.1 | Study Design

This observational, multicentered and prospective study was carried out in Centro Medico Teknon and Institut Universitari Dexeus in Barcelona, Spain during 2019–2022. The ethics committee approval reference number was 62/2019. Informed consent was obtained for all the patients.

TABLE 1 | Description of main and secondary variables.

Main variables	
20 First voice Harmonics of vocals (A, E, I, O, U) In neutral, flexion and extension positions (Hz)	
Cormack Scale grade (I, II, III; IV)	
Secondary Variables	
Demographic data	
Age (Years)	
Weight (Kg)	
Gender (Male/female)	
Height (cm)	
Body mass index (BMI)(Kg/m^2)	
ASA physical status (I, II, III; IV)	
Smoker (Yes/no)	
Sleep apnea syndrome. (Yes/no)	
COPD(Yes/no)	
Diabetes (Yes/no)	
Thyroid disorders (Yes/no)	
Background of previous difficult intubation (Yes/no)	
Airway assessment data	
Inter-incisor gap/mouth opening	> = 5 cm
	3.5–5 cm
	< 3.5 cm
Jaw protrusion grade	A
	B
	C
Thyromental distance	> = 6.5 cm
	< 6.5 cm
Neck extension range	> 100°
	90 + /- 10°
	< 80°
Arne Index	> = 11
	< 11
Voice parameters of All vocals in all positions	
Fundamental frequency (Hz)	
Jitter (Hz)	
Shimmer (dB)	
Harmonic to noise ratio, HNR (dB)	

2.2 | Patient's Selection

Randomization was not applicable as patients were consecutively enrolled upon arrival to Clinic, following the surgeon's referral, ensuring no selection bias.

2.3 | Participants

A total of 438 participants were initially enrolled in the study. After excluding 125 participants, the final analysis included 313 patients (Figure 1). The inclusion criteria were adults ASA I-III scheduled for elective surgery in need of orotracheal intubation by direct laryngoscopy. Patients with ASA > III, patients under 18 years old, emergency procedures and patients who refused to participate in the study were excluded. A total of 125 patients were excluded from the final analysis due to recent respiratory upper airway infection, nasal tone, incorrect voice recording or missing data.

2.4 | Sample Size

In AI research, conventional sample size calculations are uncommon. Instead, algorithms focus on pattern recognition and prediction using available data, prioritizing data set quality over quantity. For this exploratory pilot study, the sample size was determined by referencing similar studies on intubation difficulty using machine learning techniques such as the ones carried out by Carvalho et al. [21] and Cao S et al. [23]

2.5 | Intervention

The main and secondary evaluated variables are detailed in Table 1. A difficult airway was defined by the obtention of Cormack grades III or IV in direct laryngoscopy. During the preoperative anesthetic evaluation, the standard clinical interview for the preoperative assessment was conducted. Demographics and examination of the airway using traditional evaluation tests were collected using the department's pre-anesthetic platform for medical records. For the voice recording, the website platform voice.anestalia. com was used. Patients were asked to sit down with a straight back position facing the computer screen and were asked to put on headphones (New Bee H360 model) and locate the speaker at 5 cm from the mouth. The participants were encouraged to articulate the vocals A, E, I, O, U during 3 seconds at three different positions of the head: neutral, extension and flexion (Figure 2). The voice recordings were encoded, stored and secured in an anonymous database.

FIGURE 2 | Voice recording flowchart showing different voice recording positions and vocals. Website voice.anestalia.com (Own production).

During the intraoperative phase of the study, preoxygenation was performed with a facial mask and intubation was carried out using direct laryngoscopy (Macintosh blade 4) once adequate neuromuscular block had been ensured. The anesthesiologist evaluated the Cormack-Lehane grade of intubation for each patient and subsequently recorded it in the data collection sheet. Afterwards, the results were transferred and stored electronically in the voice.anestalia.com platform (Figure 3). Once the data was collected, the voice signal was pre-processed using MATLAB® MathWorks, R2023b Version and stored in the MySQL database by an expert in signal processing where noise or interferences were eliminated from the recording. A workflow was created using the KNIME analytics platform®, KNIME.com AG, 2006 which is a free and open-source low-code/no-code software, with the aim to build a predictive classification model for the assessment of the intubation difficulty [25]. Having previously normalized the data, different classification models such as K-Nearest Neighbors, Naïve Bayes, Neural Networks, Random Forest, Support Machine Vector and Adaboost were used. The datasets were divided into two groups: The training/validation data set, composed of 70% of the data (N = 219/313 Patients) and the test data set which consisted of the 30% of the data (N = 94/313 patients) (Figure 4). To address an imbalanced data set, the upweight minority class and oversampling of the minority class techniques were applied. Cross-validation was used to prevent overfitting, with each patient's predicted probability calculated from a model excluding that patient's data. Other techniques of dimensionality reduction such as principal analysis component (PCA) and hyperparameter tunning of the models were also applied to enhance performance of the models and provide reliable results. The following combinations of variables were evaluated including different vowels, head positions, and data demographics.

- Harmonics + demographics + vowels/positions (all cases)
- Harmonics + demographics + vowels/positions (Cormack I or IV cases)
- Spectral data + demographics (all cases)
- Demographics only (All cases)
- Harmonics only (All cases)
- Voice parameters (e.g., shimmer, jitter, HNR) + demographics (all cases)
- Voice parameters + demographics (Cormack I or IV cases)

All the models were trained and validated, and the model's performance was tested. The following metrics were extracted: F1 score, ROC AUC curve, Log-loss value, recall, precision, rate of false positive, rate of false negatives, rates of true positives and rates of true negatives as well as the overall accuracy. The model yielding the best results was selected based on these evaluations.

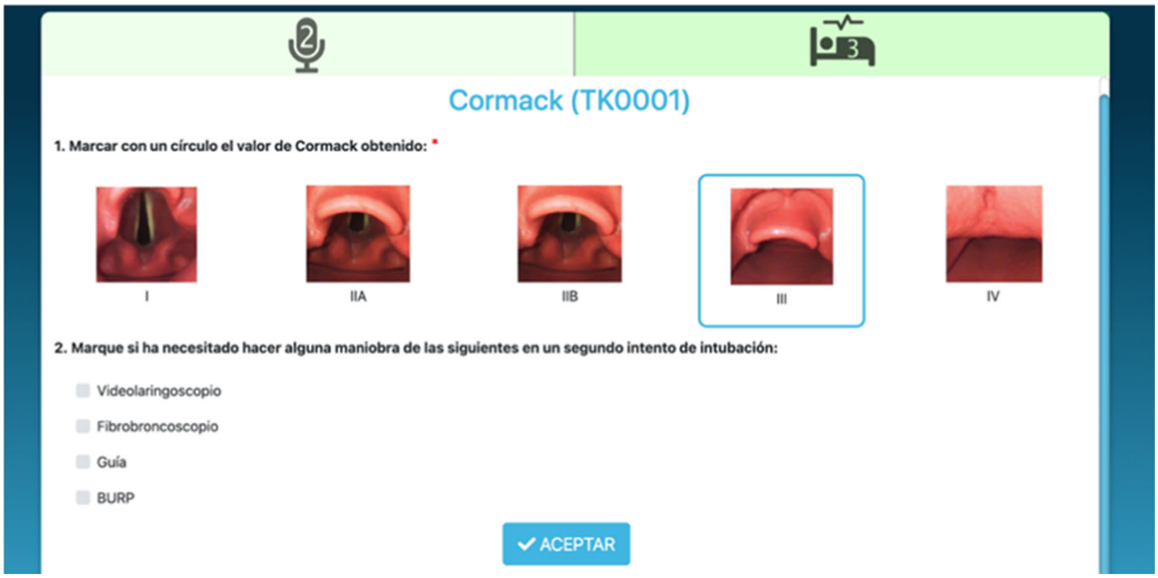

FIGURE 3 | Data collection platform (Own production).

FIGURE 4 | Data set partitioning: 70% Training/Validation and 30% test.

TABLE 2 | Demographics of all the participants included in the study.

Characteristics		N (patients)	% (percentage)
Total number of patients		313	100.00
Gender	Male	146	46.65
	Female	167	53.35
BMI	$>=25$	151	48.24
	<25	162	51.76
Smoker		105	33.55
Sleep apnea syndrome		28	8.95
COPD		3	0,96
Diabetes		19	6.07
Thyroid disorders		34	10.86
History of difficult intubation		4	1.28
Pathologies associated with difficult intubation		2	0.64
Airway pathology symptoms		2	0.64
Inter-incisors gap/Mouth opening	$>=5$ cm	271	86.58
	3,5 cm − 5 cm	41	13.10
	$<3{,}5$ cm	1	0.32
Jaw protrusion grade	A	289	92.33
	B	23	7.35
	C	1	0.32
Thyromental distance	$>=6{,}5$ cm	245	78.27
	$<6{,}5$ cm	68	21.73
Neck extension	$>100°$	288	92.01
	$90° \pm 10°$	25	7.99
	$<80°$	0	0.00
ASA	ASA I	86	27.48
	ASA II	210	67.09
	ASA III	17	5.43
	ASA IV	0	0.00
Mallampati grade	1	139	44.41
	2	111	35.46
	3	59	18.85
	4	4	1.28
Arne Index	$>=11$	22	7.03
	<11	291	92.97
Cormack grade	I	124	39.62
	IIa	98	31.31
	IIb	28	8.95
	III	45	14.38
	IV	18	5.75

2.6 | Statistical Analys

We used the KNIME platform (version 4.7) for all data analysis, leveraging its data mining and machine learning tools. Traditional statistical tests and significance levels were not applicable, as KNIME's workflows provided the necessary framework for comprehensive data processing and model evaluation.

TABLE 3 | Best combinations of parameters and binary classification models which obtained the best results for the training and testing datasets.

CORMACK STUDY		TRAINING							TESTING											
Combination	**Model**	**Accuracy**	**Precision**	**Recall**	**F1**	**Log Loss**	**AUC**	**Pr AUC**	**Log Loss**	**Accuracy**	**Precision**	**Recall**	**F1**	**AUC**	**Pr (AUC)**	**TN**	**FN**	**FP**	**TP**
HARMO-NICS + DESCRIPTIVE DATA A All positions only Cormack I and IV cases	H20 general-ized linear	0.83	0.39	0.62	0.44	0.50	0.64	0.18	0,24	0.93	0.75	0.60	0.67	0.91	0.40	37	2	1	3
VOICE PARAME-TERS + DESCRIPTIVE DATA I flexion position only Cormack I and IV cases	H20 Random Forest	0.80	0.40	0.83	0.51	0.39	0.74	0.22	0.26	0.88	0.50	0.80	0.62	0.88	0.34	34	1	4	4
VOICE PARAME-TERS + DESCRIPTIVE DATA O normal position only Cormack I and IV cases	H20 Ran-dom Forest	0.55	0.29	1.00	0.43	0.44	0.66	0.18	0.24	0.93	0.67	0.80	0.73	0.90	0.45	36	1	2	4
VOICE PARAME-TERS + DESCRIPTIVE DATA O All positions only Cormack I and IV cases	H20 general-ized linear	0.75	0.67	0.73	0.54	0.49	0.68	0.23	0.34	0.93	0.75	0.60	0.67	0.89	044	37	2	1	3

3 | Results

The final sample included 313 patients: 146 males (46.64%) and 167 females (53.35%). The mean age was 49.16 years (SD = 14.6), with an average weight of 74.53 kg (SD = 17.0) and a mean height of 168.74 cm (SD = 9.7). Most participants were classified as ASA II 67.09%, with 5.43% classified as ASA III.

For airway evaluation, 133 patients (43%) tested positive for at least one bedside screening test for a difficult airway. Additionally, 22 patients (7%) had an Arne Test Score of ≥ 11 points, indicating a higher risk. The remaining 158 patients (50%) did not test positive in the screening tests.

Comorbidities were present in 84 participants (27%), with thyroid disorders being the most common, affecting 34 patients (10.86%). Detailed demographic findings are presented in Table 2. Among the multiple models evaluated, two yielded the best performance to predict a difficult Airway: Model 1: included demographic data, vowel "A" in all positions and harmonics of the voice only analyzing Cormack I and IV cases, achieving an AUC of 0.91, F1 of 0.67, recall of 0.60, precision of 0.75, log loss values of 0.24, 2 false negatives and an overall accuracy of 0.93; Model 2: Included demographic data, vowel "O" in normal positions and voice parameters (Shimmer, Jitter, HNR); Only analyzing Cormack I and IV cases achieving an AUC of 0.90, mean F1 value of 0.73, mean recall of 0.80, a mean precision of 0.67, mean log loss values of 0.24, mean false negative values of 1 and an overall accuracy of 0.93 Table 3.

The performance results of all the classification algorithms models for assessing the ability to predict a Cormack grade III or IV (difficult Airway) can be found in the supplementary materials 1–4.

4 | Discussion

This study explores using voice analysis as an innovative predictor of a difficult airway. Previous studies focused on voice formants as predictors of difficult mask ventilation, with Carvalho et al. achieving an AUC of 0.91% for difficult laryngoscopy prediction using Mallampati and formants, and Xia et al., obtaining an AUC of 0.77% using 20 voice parameters for difficult mask ventilation [21–23]. Our study aligns with these findings but improves prediction accuracy by including additional demographics like thyroid disorders and smoking into the classification models. This study also explored harmonics, which may be more reliable than formants due to common measurement challenges [26, 27]. For this reason, we focused on normalizing harmonic amplitude, which is a multiple of the fundamental frequency, to identify and compare patterns across patients. Furthermore, KNIME®, the data analysis tool used, is able to deal with a great amount of data providing more reliable results. Matlab® was chosen over Praat® used in previous studies, for manual voice parameter extraction due to its customizable extraction capabilities [28]. Our results indicate that regarding airway evaluation, only 20% tested positive for at least one risk parameter, and only 20.13% were classified as Cormack III or IV, predicting an increased risk of airway difficulty. These findings suggest that the sample had more easy than difficult airways, creating an imbalanced data set, which required balancing techniques before introducing the data into the model. Given that algorithms more easily detect differences between extreme cases, it's unsurprising that the best results were achieved by analyzing only Cormack I and IV. Models including all Cormack grades (I-IV) performed worse, likely due to fewer distinct differences between intermediate cases

The models showed strong performance across various metrics (AUC, F-1 score, accuracy, precision, recall). However, when only harmonics were used without descriptive data, performance declined significantly. Similarly, using demographic information alone only yielded an AUC of 0.56 indicating limited effectiveness for accurate classification or prediction. This suggests that neither voice analysis nor demographics alone are sufficient for reliable classification; however, combining voice parameters with demographics enhances classification accuracy for a difficult airway.

Although Mallampati has variable sensitivity and specificity, it remains widely used in clinical practice [29], the data shows that using voice as a predictor could offer a more convenient and accessible method for airway assessment, potentially reducing the need for physical exams and improving efficiency and patient outcomes

Furthermore, one of the main limitations is a small sample size. Another one is that voice parameters exhibit significant individuals' variability and have been shown to be influenced by a variety of factors such as gender or certain conditions which may have affected our data analysis [30]. For this reason, external validation to ensure the reproducibility of the results is needed. Additionally, given the increasing adoption of videolaryngoscopes, it would also be valuable to investigate the potential of voice analysis for predicting difficult airways using these devices.

5 | Conclusion

In conclusion, our results offer a novel approach to preoperatively predicting a difficult airway, with the potential for use in telematic preanesthetic consultations. Voice acoustic parameters combined with clinical characteristics show promise in machine learning algorithms for predicting a difficult airway, suggesting its potential as a predictive tool. However, further refinement of the algorithm is needed to enhance its performance and utility.

Author Contributions

Claudia Rodiera: conceptualization; data curation; formal analysis; investigation; methodology; resources; writing–original draft. **Helena Fortuny:** data curation; formal analysis; software. **Adaia Valls:** supervision; writing–review & editing. **Rosa Borras:** supervision; writing–review & editing. **Carlos Ramírez:** supervision. **Bibiana Ros:** supervision; writing–review & editing. **Josep Rodiera:** conceptualization; supervision; writing–review & editing. **Jesús Santaliestra:** supervision. **Miquel Lanau:** software; supervision. **Nacho Rodríguez:** supervision.

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Disclosure

The lead author Claudia Rodiera affirms that this manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Data Availability Statement

The authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials, additional data from the corresponding author are available under request. The authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials. All references cited in this manuscript have been carefully checked. None of the cited articles have been retracted or corrected as of the date of submission. Any corrections issued have been evaluated and do not affect the relevance of the citations for this article.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.