Expert System Design for Automated Prediction of Difficulties in Securing Airway in ICU and OT

D. K. Sreekantha[1(✉)], H. K. Rachana[1], Sripada G. Mehandale[2], Mohammed Javed[3], and K. V. S. S. S. S. Sairam[4]

[1] Department of CSE, NMAM Institute of Technology, Nitte, Karnataka, India
sreekantha@nitte.edu.in
[2] Anaesthesiology and Critical Care Unit, KSHEMA, Mangalore, Karnataka, India
[3] Department of IT, Indian Institute of Information Technology, Allahabad, India
[4] Department of E&CE, NMAM Institute of Technology, Nitte, Karnataka, India

Abstract. The maintenance of uninterrupted patient respiratory passage (airway) and unhindered breathing is the primary duty of an anesthesiologist or other physicians involved in patient care under emergency trauma or surgical procedures in ICU (Intensive Care Unit) and Operation Theatre (OT). Anesthesiologist should ensure the full control over the patient airway management either bypassing an endotracheal tube or any other similar devices. The unanticipated difficulties in airway management are the most important contributors to airway related mishaps, if these are not managed effectively may lead to death or permanent bodily harm to the patient due to inadequate oxygenation. The recent survey reports revealed that 53% of anaesthetic deaths are either airway or respiratory related. Incidence of difficult airway among patients has been predicted to be in the range of 1.1 to 3.8%. This paper aims at identifying all the critical risk parameters contributing to difficult airway and subsequently developing a framework to automate the prediction of difficult airways well in advance. Authors have designed an expert system prototype for predicting the difficulties in airway management and suggesting appropriate remedies using machine learning algorithms.

Keywords: Difficult airway · Endotracheal intubation · Anaesthesia · Laryngoscopy · Prediction · Intensive Care Unit (ICU) · Decision tree · Machine learning · Expert system and knowledge base

1 Introduction

The term airway [1] is defined as the passage for air from external nares (nostrils) or lips to alveoli in the lungs, upper airway and extra-pulmonary portion of this passage consisting of the nasal and oral cavities, pharynx, larynx, trachea and large bronchi.

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The term difficult airway is defined by American Society of Anaesthesiologists (ASA) as a clinical condition in which generally trained anesthesiologists have a skill to analyse the difficulty with the mask ventilation or with the tracheal intubation or both. Competence in airway management is an important medical specialty.

The primary objective of anesthesiologist should be to make every possible effort to ensure secure airway in the very the first intubation attempt successfully with good confidence. It is very important to assess patients for both difficult mask ventilation as well as intubation. Airway management is ensuring safe anesthetic routine and in most of the cases it is uncomplicated [2]. It has been acknowledged for lot many years that, the occurrence of difficulty in airway management can result in serious consequences [3]. Difficult airway management has two vital ways mask ventilation or providing air or oxygen to lungs using a bag filled with breathing gases, mask fitting over nose and mouth [4]. The process of passing tube into trachea (endotracheal tube) is called endotracheal intubation. Endotracheal intubation is very often performed for a period of mask ventilation with 100% oxygen before undertaking any definitive airway management. This helps in overcoming preexisting oxygen deficiency or increase oxygen stores to tide over the duration of laryngoscopy and intubation during which patients are not able to breath. The passing of an endotracheal tube is to convey respiratory gases from outside in to lungs of patients with depressed consciousness, victims of physical trauma, infection, or cancerous growth in the upper airway. This passing of tube is required to support the breathing (respiratory failure mandating ventilator support) and for those undergoing surgery under general anaesthesia. This endotracheal intubation requires a clear view of larynx (sound box), which is generally by direct vision using a device called laryngoscope. This clear vision of larynx demands aligning oral, pharyngeal and laryngeal axes, which is not straight forward affair in majority of patients. The difficult airway occurs in some individuals for various reasons ranging from facial skeletal anomalies, infections leading to swellings in and around the face, decreased mouth opening, growth around the airway, decreased neck mobility and obesity. In such cases the airway management may become difficult or sometimes impossible [5].

The recent survey [6] reported that 53% of anesthetic deaths are either airway or respiratory related. A study by anaesthesia residents in 2012 discovered that first-pass success rates did not stabilize until they perform more than 150 intubations [7]. The general anesthesia may lead to direct or indirect airway damage. Direct damage is caused by necessary or excessive force applied on airway instrumentation or injury during airway device insertion or removal. Indirect damages are inadequate oxygenation, ventilation and such injuries may overlap with respiratory problems [7]. The difficult tracheal intubation elucidate 17% of the respiratory related injuries with the consequences in notable morbidity and mortality [3]. Any delay in resumption of oxygenation during an attempt to secure the airway (failed mask ventilation or failed intubation or both) can result in severe damage from temporary to permanent brain damage or death. In fact, about 28% of all anesthesia related deaths are subordinate to the inability to mask ventilate or intubate [15]. The mask ventilation is the fundamental component of airway management and in case of difficult intubation, it serves a major role [11]. American Society of Anesthesiologists (ASA) data suggested that one third of most common respiratory problems lead to brain damage and patient death [19]. In United Kingdom in the year 2011, 4th National Audit Project (NAP4) inspected anesthesia related primary airway complications and discovered 50 obstructed airway cases [24].

This inspection revealed that one of the most important causes of airway related mishaps were poor assessment of airway, prior to airway intervention. Acute airway obstruction is considered as medical emergency which potentially resulting in serious morbidity and mortality. The difficult airway being multifactorial, several assessment tools were studied, but none of them were found fully satisfactory till date. The two most commonly employed tools for airway difficulty prediction are Mallampati and Wilson score correlating with Cormack Lehane grading [16]. These methods considered the various parameters associated with difficult tracheal intubation, extubation and mask ventilation. Some of difficult airway parameters are mouth opening, head and neck movement (atlantoocipital joint assessment), Mallampati classification and receding mandible, protruding maxillary incisors (buck teeth), thyromental distance, sternomental distance, obesity, history of difficult intubation, extubation and mask ventilation [4].

Authors have carried out an extensive study of literature and identified critical risk parameters leading to difficult airway management. These risk parameters are organized in a hierarchical frame work for prediction of difficulties. These risk parameters are assigned the weights based on their impact in prediction of difficulty in decision making. The set of rules governing the decisions are studied from doctors and incorporated in to rule base. The actual representative sample data from patients is gathered by doctors in KSHEMA and given to us for study. Authors have simulated large data set using these samples. This data set processed using algorithms in Intel distributed Python toolbox.

Rest of this paper is organized in to sections. Section 2 focuses on Recent related work is dealing with discussion on work carried out by earlier researchers in this area. Section 3 discusses on Proposed Expert system methodology adopted by the authors. Section 4 has description on Data preparation and Implementation of various machine learning algorithms using Intel Distributed Python tools. Section 5 deals with Results discussion. Authors have given their Conclusions on their study in the last section of the article.

2 Recent Related Work

The summary of literature review carried out by the authors is presented in this section. The expert system is software that imitates the decision making competency of a human expert. A special framework of risk parameters was designed to predict the hepatitis contamination [8]. An information based expert framework with an objective to provide the restorative exhortation to the patients and the essential information about the diabetes was also designed [9]. This framework incorporates a new learning experience about the sustenance, exercise, medicine and how to deal with the glucose levels. The identification of difficult airway parameters related to intubation and extubation in adults was studied [7]. This paper explored the issues related to surgical operation tubes and tube displacement. The critical care physicians are required to be conversant with difficult airway algorithms and pertinent airway adjuncts. The nursing expert system fundamentally served the general population living with diabetes particularly in provincial territories [10].

This system educates the patient about the background for appropriate diagnosis and treatment. This expert system utilizes a rule-based reasoning technique through easy querying of symptoms, signs and examination carried out on the patient. The expert system is used for diagnosing heart diseases in patients to facilitate treatment. The applications of decision support systems are explored in medicine, anaesthesia, critical care and intensive care medicine [11]. Airway management can be divided into three regions i.e. the upper, middle and lower regions. These regions can be correlated with difficult laryngoscopy, intubation and mask ventilation consequently [12]. The main objective of laryngoscopy is to produce an eminent perspective of vocal cards to easily perform the intubation. The airway difficulties can lead to morbidity and mortality. The doctors during clinical examination of the airway can observe several distinguishing features such as tempero mandibular joint mobility, decreased neck mobility (Delilkan test).

The respiratory events are the most basic reasons for the anesthetic related injuries such as dental damage. The main causes for the respiratory related injuries are inadequate ventilation, oesophageal intubation and difficult tracheal intubation [13]. The doctor conducts general physical and regional examination such as mouth opening, neck extension, Mallampati test, Patil's thyromental distance, neck circumference. LEMON method of airway assessment is looking for congenital anomalies, radiographic assessment, quick airway assessment, for the prediction of difficult airway. Cormack Lehane grading of laryngoscope view conveys the difficulty in having proper vision of larynx and feasibility of endotracheal intubation. One single test cannot provide a prediction of high sensitivity and specificity, as a result it should be a composition of multiple tests. In the event of an unanticipated difficult airway, anesthesiologists must be well prepared with a combination of practical and pre-formulated methods for the airway management. The tracheal re intubation in patients is found to be more complex, because it includes several parameters associated with hypoxia, haemodynamic problems, hypercarbia, agitation and airway obstruction [14]. The different parametric concepts correlated with the mechanism of tracheal intubation mainly in children was also studied [15]. This study on the problems involved in the pediatric airway management difficulties with unsuccessful endotracheal intubation or the mask ventilation, and the immediate causes of mortality and perioperative morbidity was carried out [16]. This study attempts to predict the difficulty in tracheal intubation and direct laryngoscopy among the newborn. The authors followed one of the most generally used algorithm mainly from the American society of Anesthesiology (ASA) in 2013 which mainly helps to describe the difficult airways. Most of the difficult airway problems in children can be easily predicted. The definite mechanism to preserve the airway patency and ventilation control, is intubation laryngoscopy and trachea mechanism that helps to identify the difficult airway. The observational study to determine the prediction, incidence and outcomes leading to impossible mask ventilation was carried out on the adult patients over a period of four years [17]. The primary outcome of this study was to classify impossible mask ventilation and secondary outcome was direct laryngoscopic views and the difficult airway management techniques.

The cross-sectional study to correlate a preanesthetic evaluation to predict a difficult intubation with the certain conditions are met at laryngoscopy and endotracheal intubation were also carried out [18]. The data of eighty one patients submitted to general anesthesia was examined at a preanesthetic consultation in accordance with modified Mallampati classification, Wilson score and American society of anesthesiologists (ASA) difficult airway algorithm. The advantages of applying Mallampati and Wilson's grading for the prediction of difficult laryngoscopy and intubation were studied [19]. The goal of this study is to estimate the accuracy of the modified mallampati test and the Wilson score for predicting difficult tracheal intubation. The comparative study of Wilson score, modified mallampati and Cormack Lehane grading was carriedout. The association and accuracy of CLT (cuff-leak-test) only or associated with another laryngeal parameter with PES has been primarily determined [20]. In a medical surgical intensive care unit 51 mechanically ventilated adult patients were tested.

The observations from extubation using CLT, laryngeal ultrasound and indirect laryngoscopy recorded the parameters of biometric, laryngeal and endotracheal tube (ETT). No single form of the CLT or PES have accurately predicted the combination with laryngeal parameters. The applications of different airway devices for emergency airway management in endotracheal intubation reported complications occurred [21]. The authors suggested to airway passage consultants (non-physician and physician providers) to plan out the successful intubation in very first pass intubation attempt. The prehospital airway management using supraglottic airway devices and procedural experiences, success rates of intubation are analyzed [15]. Author's main goal was to find the relation between the system-wide initiation of king LT and ETI success rates. The retrospective observational study from 37 Emergency Medical Service (EMS) agencies within a country division of south western Pennsylvania was carried out. The orotracheal intubation [10] is mainly received by fewer patients with advanced airway management by introduction of knowledge based expert system. The authors stated that this system helps the patients by educating them about diabetes and also provides the medical advice. This system is highly useful because doctors don't have a time to explain about the symptoms and risk factors to the diabetic patients and it educates them about food, exercise, medication and how to manage the blood sugar levels [15]. Authors have compared the advantages Mallampati and Wilson's grading for the prediction of difficult in laryngoscopy and intubation. Researchers have discussed systematically airway prediction of difficulties in mask ventilation. They have compared the accuracy of the modified Mallampati test, Wilson score for predicting difficult tracheal intubation [22]. Authors have studied Cormack Lehane grading and presented an efficient heart disease prediction system using data mining. This paper discussed cardiovascular disorder which is a considerable reason for mortality and in the current living style. The main objective of this study is to help a non-specialized doctors to make correct decision about the risk level in heart diseases. Authors proposed to use KEEL (Knowledge Extraction Based on Evolutionary Learning). KEEL is an open source (GPLV3) Java programming apparatus mainly used to implement developmental process for data mining issues.

The literature study enabled authors have discover that many researchers have worked to identify, classify the various risk parameters in predicting difficult airway in children and adults. Researchers have studied the difficult mask ventilation, intubation cases. The comparative study of Mallampati and Wilson's grading and AAS algorithms was carried out. The expert systems solutions developed for diabetics and heart diseases were studied. This study has enriched the knowledge of authors and given the insight in to the identification, classification of difficult airway risk parameters and conception of expert system for prediction of difficult airway, well in advance by novice doctors.

3 Proposed Methodology

3.1 Proposed Expert System Approach

Authors have discovered the urgent need for the facility to retrieve and correlate similar cases from a centralized airway patient database. This facilitate to predict and enable self learning/training in assessment of difficult airway before the actual surgical procedure. This capability would help the novice doctors for managing airway in a professional way. The survey reveals the main reason for unanticipated difficult airway is the lack of systematic study of patient's physical parameters and the lack of technology support. So authors aimed at designing the prototype expert system. This proposed expert system has user friendly interface thorough which user enters input the physical risk parameters. The inference engine processes these input parameters and determines the difficult airway risk levels. This expert system has knowledge base that facilitates the users to retrieve and relate similar cases from a centralized knowledge base to predict difficult airway. The expert system has self learning capability to update the new cases. A novice anesthesiologists are advised to take the help of this expert system for assessing the difficult airway, before the actual surgical procedure. In summary from techno medical point-of-care project this paper's first objective is to save the patient from complications (like damage of lungs, breathing problems) and inadequate oxygenation that arise because of shortcomings in managing difficult airway. Second objectives is to design an expert system to support the novice anesthesiologist to perform like expert anesthesiologist using this expert system tool. This expert system boosts the confidence of the novice doctors to manage the eventuality by helping them to understand the situation in advance and accordingly enabling them to manage the surgical complications.

3.2 Architecture of Proposed Expert System Design

Authors have discussed with doctors from the department of Anaesthesia and Critical care of K.S. Hegde Medical Academy, Mangalore and understood the manual process of airway management. At present in manual system anaesthesian diagnoses the patient's physical parameters and applies the sequence of airway techniques with increasing order of difficulties or risk in airway management. Anaesthesian first checks if mask ventilation is possible, then carries out mask ventilation. Only when mask ventilation is not possible, then doctor proceeds checking for Supraglottic airway, Laryngoscopy and Intubation, Extubation one after the other in increasing order of difficult airway risk. These interactions with doctors and visit to hospital has enriched the authors to conceive the design of an expert system prototype for airway management. The architecture of proposed expert system is shown in Fig. 1.

Anaesthesian examines the patient who has to undergo airway management treatment and records the patient physical parameters to assess whether there is any symptoms for difficulty airway. In the case of unpredictability in difficult airway, doctors calls for the support from expert systems. The physical airway parameters of the patient are feed in to the expert system through user interface. The inference engine processes this physical parameter data and predicts the difficulties in airway management. The expert system advises doctors through SMS and mails along with the detailed assessment report. This report contains the information about which airway technique to apply and gives justification as to why doctor has to apply that particular technique to that patient. This system is designed to help novice doctors to take better airway related decisions because there is an acute shortage of expert anaesthesian nationally (Fig. 2).

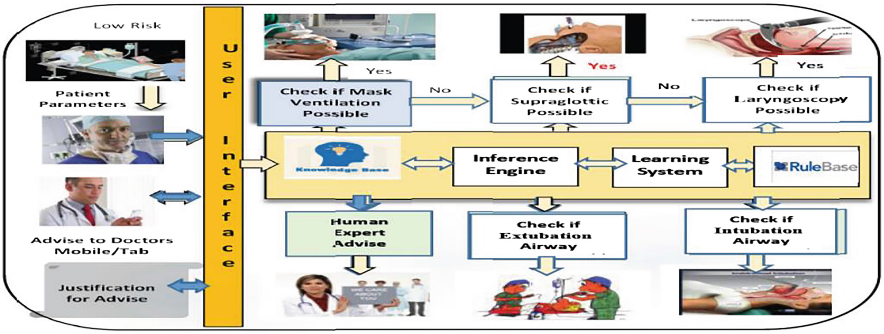

Fig. 1. Architecture of airway management expert system

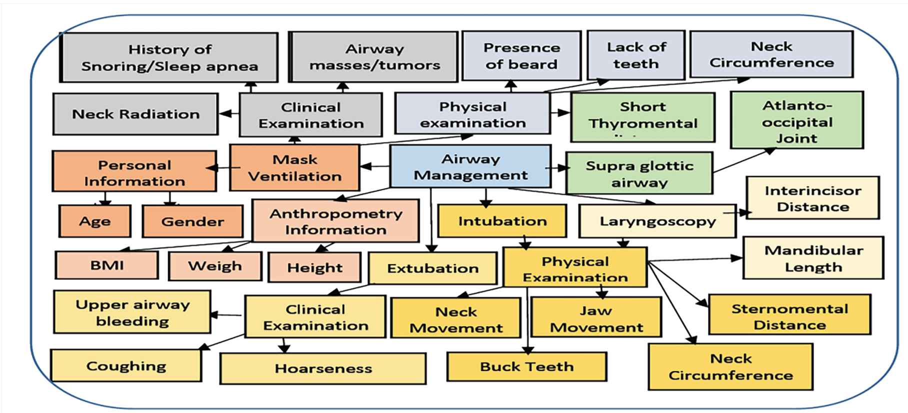

Fig. 2. Architecture of airway management physical parameters

3.3 Architecture of Airway Management Physical Parameters

Authors have discussed with expert anaesthesian and identified all the parameters associated with difficult airway. These parameters are organized based on their significance and features as shown Table 1.

3.4 Patients Physical Airway Parameters Associated with Difficult Mask Ventilation

The difficult airway risk parameters for different airway techniques such as mask ventilation, laryngoscopy, supraglottic airway, intubation and extubation have been studied and classified by the researchers. The following Tables 1 and 2 shows the parameters, descriptions and corresponding standard values. The difficult airway parameters for Mask Ventilation and their description are listed in the Table 1.

Table 1. Physical airway parameters of difficult mask ventilation

Sl. no	Parameter	Grades	Predictive value	Prediction level	Difficulty decision
1.	BMI (Body Mass Index)	Grade 0	<18.5	Normal	Easy
		Grade 1	18.5–24.9	Mild	Slightly difficult
		Grade 2	25–29.9	Moderate	Difficult
		Grade 3	30 or 50	Significant	Very difficult
		Grade 4	Greater	Severe	Impossible
2.	Mallampati Grade (It was performed with the patient in the sitting position, the neck held in the neutral position and the tongue fully protruded without phonation)	Grade 0	Tip of the Epiglottis is seen, Tonsils, Pillars and Soft palate are clearly visible.	Normal	Easy
		Grade 1		Mild	Easy
		Grade 2	The uvula, pillars & upper pole are visible	Moderate	Slightly difficult
		Grade 3	Only part of the soft palate is visible	Significant	Difficult
		Grade 4	Only the hard palate is visible	Severe	Impossible
3.	Weight (Weight of patient) is the main parameter of the intubation?	Minimum Standard Maximum	<1–90 kg 90–110 kg >110 kg	Normal Moderate Severe	Easy Difficult Impossible
4.	Neck Circumference (Measured using a flexible tape at the level of the cricoid cartilage while patient is in the sitting position with the head and neck in the neutral posture)	Grade 0	<=44 cm	Normal	Easy
		Grade 1	>44 cm	Moderate	Slightly difficult

(*continued*)

Table 1. (*continued*)

Sl. no	Parameter	Grades	Predictive value	Prediction level	Difficulty decision
5.	Mandibular length	Grade 1	>9 cm	Normal	Easy
		Grade 2	<=9 cm	Moderate	Slightly difficult
6.	Interincisor Distance (The patient is asked to open his/her mouth as wide as possible, the distance between the upper and lower incisors was measured)	Grade 1	>4 cm	Normal	Easy
		Grade 2	<=4 cm	Moderate	Slightly difficult
7.	Thyromental distance (Measured by a small cricket ruler with the head fully extended and the mouth closed)	Grade 1	>6.5 cm	Normal	Easy
		Grade 2	<=6.5 cm	Moderate	Slightly difficult
8.	Sternomental distance	Grade 1	>13.5 cm	Normal	Easy
		Grade 2	<=13.5 cm	Moderate	Slightly difficult

Table 2. Parameters for difficult mask ventilation and their standard values

Sl. no	Risk parameters	Description
1	Increased Body Mass Index (BMI)	Over weight of the body
2	Presence of beard	Creates problem for mask seal to fit correctly
3	Lack of teeth	No teeth
4	Age (Greater than 55 years)	Advanced age (age > 55) is also associated with difficulty for mask ventilation
5	Male gender	This problem is mainly found in male
6	Airway masses/tumors	This problem is mainly causes difficulty in mask ventilation
7	Mask seal	Mask seal is important, so any feature that may interfere with this component of mask ventilation such as beard are important to note
8	Obesity/A history of airway obstruction	Obesity or history of airway obstruction such as obstructive sleep apnea
9	Shrinking of corners of mouth	One of the reasons for difficult mask ventilation is ill fitting of mask due to slagging of cheek and shrinking of corners of mouth in edentulous patients

(*continued*)

Table 2. (*continued*)

Sl. no	Risk parameters	Description
10	History of snoring, sleep apnea or stiff lungs	Edentulous patients due to poor mask seal and those with stiff lungs (such as smokers or those with COPD) will also find it difficult to ventilate. A history of snoring is related to obesity & OSA obstruction with the muscles of the Orthodox are relaxed, during the sleep & likely during sedation/Anesthetists

The Table 2 above shows the identified risk parameters and their standard description. These values are used in designing the rule base and data set validation.

3.5 Rulebase Design

Researchers have studied from expert anaesthesian/doctors, the risk parameters and designed the set of rules that are to be followed by while managing the difficult airway. This organized set of rules are called a rule base. Expert systems are using this rule base for processing the input and interpreting output. Authors have designed the rule base by considering five different hierarchical categories of airway management from minimum to maximum risk levels. The minimum risk is associated with mask ventilation, next risk is supraglottic airway, next is laryngoscopy, highest risk is intubation and extubation. If first method is not successful, then we move on to the next higher risk methods.

Table 3. Sample Fuzzy Logic rule base for mask ventilation

Rule no.	Antecedent- IF	Consequent- THEN
1.	Patient is Elder AND Gender is Male AND BMI is higher side	Patient is in a mild condition, Mask ventilation is difficult
2.	Patient is Elder AND Gender is Male AND Beard is Present	Patient is in a mild condition, Mask ventilation is difficult
3.	Patient is Elder AND Gender is Male AND Mallampati III or IV grade is visualized	Patient is in a mild condition, Mask ventilation is difficult
4.	Patient is Elder AND Gender is Male AND Neck radiation is high	Patient is in a severe condition, Mask ventilation is impossible
5.	Patient is Elder AND Gender is Male AND Lack of teeth factor have been observed	Patient is in a mild condition, Mask ventilation is difficult
6.	Patient is Elder AND Gender is Male AND Airway masses/tumors have been seen	Patient is in a mild condition, Mask ventilation is difficult
7.	Patient is Elder AND Gender is Male AND BMI is increased AND Airway masses/tumors have been observed	Patient is in a moderate condition, Mask ventilation is difficult

(*continued*)

Table 3. (*continued*)

Rule no.	Antecedent- IF	Consequent- THEN
8.	Patient is Elder AND Gender is Male AND BMI is increased AND Obesity have been increased	Patient is in a moderate condition, Mask ventilation is difficult
9.	Patient is Adult AND Gender is Male AND BMI (Grade 0) is low	Patient is in a normal condition, Laryngoscopy is easy
10.	Patient is Adult AND Gender is Male AND Neck Circumference is very low AND Mandibular length is very low AND Interincisor Distance is very low AND Thyromental Distance is very low AND Sternomental Distance is very low	Patient is in a moderate condition, Laryngoscopy is difficult
11.	Patient is Adult AND Gender is Male AND Neck Circumference is very low	Patient is in a moderate condition, Laryngoscopy is difficult
12.	Patient is Adult AND Gender is Male AND Mandibular length is very high	Patient is in a severe condition, Laryngoscopy is impossible
13.	Patient is Adult AND Gender is Male AND Mandibular length is very high	Patient is in a severe condition, Laryngoscopy is impossible
14.	Patient is Adult AND Gender is Male AND Interincisor Distance is very high	Patient is in a severe condition, Laryngoscopy is impossible

Table 4. Patient age classification

Sl. no.	Age linguistic value	Range of age in years
1.	Child	1–12
2.	Teenager	13–19
3.	Adult	20–39
4.	Middle aged	40–50
5.	Elder	51–69
6.	Old aged	70 Onwards

Table 5. Summary of airway safety rules

Sl. no	Safe level	Hierarchical order	No. of rules
1.	1st safe level	Mask ventilation	111
2.	2nd safe level	Supra glottic airway	5
3.	3rd safe level	Laryngoscopy	47
4.	4th safe level	Intubation	94
5.	5th safe level	Extubation	23

3.6 Rulebase for Mask Ventilation

Authors have designed few hundred rules for various techniques of airway management using Fuzzy Logic. The sample rules for mask ventilation are shown in Table 3. These rules are based patients age, gender and other physical parameters such as neck circumference etc. for predicting the difficulty in mask ventilation and laryngoscopy. The patient's current age is also one of the risk factor which is fuzzified and shown in Table 4. Authors have designed rules for each airway management technique. Table 5 shows the number of rules designed for each airway management.

4 Expert System Implementation

4.1 Software Tools Used

Authors have used Intel distributed python tools for building the prediction of airway difficulties. Intel distributed python tools are easy to learn, use, have an extensive library support that enables users to perform complex analysis. Anaconda tools provides iPython Notebook that supports us to code in Python. iPython notebook contains many cells where user can readily write code and add comments (in Markdown) to a cell. The notebook is displayed right into your web browser.

4.2 Patient Data Processing

The difficult airway parameter data is classified in to five stages like Mask ventilation, intubation and Laryngoscopy, Extubation, and Supraglottic airway. The patient data about these five difficult parameters are collected. The units for measuring these parameters are represented as numerical values. These parameter values are used as features for classification. The doctors from KSHEMA have provided actual patients data collected from their database for training and testing of the expert system model. The range of parameter data values varies from Indian patients and other country patients. The collected data set is in Comma Separated Values (CSV) format file.

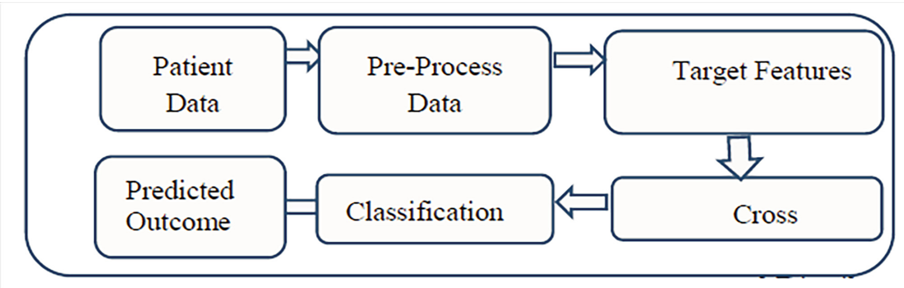

Fig. 3. System flow showing steps in prediction of difficult airway Intel Distributed Python package

The Steps in Data Experimentation
The patient data is cleaned, checked for categorical values (if any) and converted to numerical data. This process is performed using a technique called One Hot Encoding, which is important step because a few classifiers in scikit-learn work only with numerical values. Authors have conducted experiments to predict the difficulty associated with intubation airway management. The step by step followed in conducting experiment and outcome of each step is described below in Fig. 3.

```
In [8]: df1['Prediction'] = df1['Prediction'].map({'E':0,'D':1})
        df1.head()
```

Out[8]:

	Sl.No	Age at initial pathologic diagnosis	Weight	C-L (Grade 3 or 4)	Mallampati score	Interincisor gap	Retrognathia	Buck teeth	Prediction	Thyromental distance	Cervical joint rigidity
0	1	40	110	High	Low	Low	Moderate	Absent	1	6.5	High
1	2	41	90	High	Low	Low	Moderate	Absent	1	6	High
2	3	42	75	Low	High	High	Absent	Absent	0	7	Low
3	4	43	65	Low	High	High	Absent	Absent	0	8.5	Low
4	5	18	85	High	High	High	Moderate	Absent	1	3.7	High

Fig. 4. Load the pre-processed patient parameters data

Target Feature Identification

After pre-processing, all the parameter columns except prediction field is considered as the features. Prediction column is taken as the target.

Step-1 Load the libraries and patient parameters data

Step-2 Reading input parameter data

This input CSV file is read into python using the Jupyter integrated development environment. As shown in Figs. 4 and 5. The Fig. 5 shows the list of parameters data such as patient weight, age, cl grade, buck teeth, mallampati score are inputs to the system and prediction column shows prediction outcome of airway is difficult or easy for selected 20 patients.

```
In [4]: df1
```

Out[4]:

	Sl.No	Patient id	Age at initial pathologic diagnosis	Weight	C-L (Grade 3 or 4)	Mallampati score	Interincisor gap	Retrognathia	Buck teeth	Prediction	Thyromental distance	Cervical joint rigidity
0	1	IMM01	40	110	High	Low	Low	Moderate	Absent	D	6.5	High
1	2	IFM02	41	90	High	Low	Low	Moderate	Absent	D	6	High
2	3	IMM03	42	75	Low	High	High	Absent	Absent	E	7	Low
3	4	IFM04	43	65	Low	High	High	Absent	Absent	E	8.5	Low
4	5	IMT05	18	85	High	High	High	Moderate	Absent	D	3.7	High
5	6	IFT06	19	75	High	High	High	Moderate	Absent	D	5.3	High
6	7	IMT07	16	55	Low	Low	High	Absent	Moderate	D	8	High
7	8	IFT08	14	57	High	Low	High	Moderate	Severe	D	3.9	Low
8	9	IMM09	45	90	Low	Low	Low	Moderate	Absent	E	7.1	Low
9	10	IFM10	47	95	Low	Low	Low	Moderate	Absent	E	6.8	Low
10	11	IME11	52	100	Low	High	Low	Absent	Moderate	D	2.9	Low
11	12	IFE12	51	94	Low	High	High	Absent	Absent	E	6.6	Low
12	13	IME13	55	85	NT	NT	NT	NT	Absent	E	NT	NT
13	14	IFE14	53	70	NT	NT	NT	NT	NT	E	NT	NT
14	15	IME15	61	81	High	NT	NT	NT	NT	D	NT	NT
15	16	IFE16	63	74	High	NT	NT	NT	NT	D	NT	NT
16	17	IME17	60	69	Low	NT	NT	NT	Absent	E	NT	NT
17	18	IFE18	59	67	Low	NT	NT	NT	Moderate	E	NT	Low
18	19	IMM19	46	116	NT	NT	NT	NT	Absent	D	NT	Low
19	20	IFM20	47	112	NT	NT	NT	NT	Absent	D	NT	Low
20	21	IMM21	48	109	Low	Low	Low	Severe	Absent	D	7.3	Low

Fig. 5. Input Patient Data set loaded

Step-3 Cross validation split

The data set is split into two subsets. 70% of the data is used for training and 30% is used for testing. This split is done using the Stratified Shuffle Split function from cross validation module of Scikit-Learn

Step-4 Classification

The Scikit-Learn python tool provides a wide variety of machine learning algorithms for the classification. Ten classifiers from the package were used for the study: Decision Tree classifier, Gaussian NB, SGD Classifier, SVC, K Neighbors Classifier, One Vs Rest Classifier, Quadratic Discriminant Analysis (QDA), Random Forest Classifier, MLP Classifier, and AdaBoost Classifier. Keeping the default environment intact the accuracy of each classifier is recorded using the scikit-learn package of python.

Setp-5 Prediction outcome

After processing data with prediction rules by the inference engine. The predictions classified as easy or difficult airway. The conclusions are drawn based on the risk parameter values of those five stages.

5 Results Analysis

The final results after experimentation with this prototype are shown in Fig. 6. The difficult airway outcome is encoded with symbol 0 as easy and symbol 1 as difficult. The numerical airway parameters values are converted into fuzzy linguistic values ranging from LOW, Moderate and High. Age and weight of the patient pathologic diagnosis, Weight and C-L grade are shown in Fig. 6. Three patients with serial number 1, 12 and 45 are predicted as having difficult airway rest are having easy airway passage.

In [8]:
```
df1['Prediction'] = df1['Prediction'].map({'E':0,'D':1})
df1.head()
```

Out[8]:

	Sl.No	Age at initial pathologic diagnosis	Weight	C-L (Grade 3 or 4)	Mallampati score	Interincisor gap	Retrognathia	Buck teeth	Prediction	Thyromental distance	Cervical joint rigidity
0	1	40	110	High	Low	Low	Moderate	Absent	1	6.5	High
1	2	41	90	High	Low	Low	Moderate	Absent	1	6	High
2	3	42	75	Low	High	High	Absent	Absent	0	7	Low
3	4	43	65	Low	High	High	Absent	Absent	0	8.5	Low
4	5	18	85	High	High	High	Moderate	Absent	1	3.7	High

Fig. 6. Airway difficulty prediction based on input data

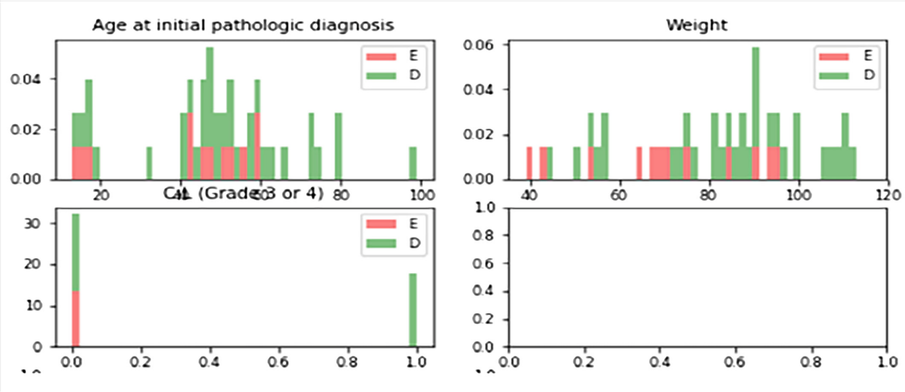

Fig. 7. Histogram showing the Age and Weight relationships

Mean values of age at initial pathologic diagnosis, weight and C-L grade are used in the classification of the intubation airway technique is shown in Fig. 6. Higher values of these parameters tend to show a correlation with difficult airway surgery. Mean values of thyromental distance, Mallampati scores and buckteeth does not show a particular preference of one technique over the other. In any of the histograms there are no noticeable large outliers that warrants further cleanup as shown in Fig. 7.

Logistic Regression Model

Logistic regression is widely used for classification of discrete data. This algorithm uses only binary (1, 0) for classification. Based on the observations in the histogram plots in Fig. 7, Authors have reasonably hypothesized that the airway problem prediction depends on the mean age at initial pathologic diagnosis, mean weight, mean thyromental distance, mean C-L grades and mean neck circumference. Authors then performed a logistic regression analysis using those features as follows, the prediction accuracy is 89.444% which is reasonable. The accuracy of the predictions is good but not great. The cross validation scores are reasonable.

```
predictor_var = features_mean
model = RandomForestClassifier(n_estimators=100,min_samples_splits=20, max_depth=7, max_features=2)
classification_model(model,traindf1,predictor_var,outcome_var)

---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-3-e1f7f67a384d> in <module>()
----> 1 predictor_var = features_mean
      2 model = randomForestClassifier(n_estimators=100,min_samples_splits=20, max_depth=7, max_features=2)
      3 classification_model(model,traindf1,predictor_var,outcome_var)
```

Fig. 8. Screen shot of Random Forest algorithm experiment

Accuracy from Random Forest algorithm is: 95.72

Random Forest Model

This algorithm uses all the features and improves the prediction accuracy to 95.729% and the cross-validation score is great. An advantage with Random Forest model is that it returns a feature importance matrix which can be used to select features as shown in Fig. 8.

The authors have experimented with four different algorithms and discovered that Random Forest prediction algorithm works best with 95.72% prediction accuracy compared to other three algorithms as shown Table 6.

Table 6. Comparison of accuracy by different algorithms for the prediction

Sl. no	Classifier algorithm	Accuracy %
1.	Logistic regression model (Training data)	89.44
2.	Random forest (Training data)	95.72
3.	Decision tree (Training data)	96.98
4.	Random forest (Test data)	95.72

6 Conclusions

Authors have studied the literature on airway management from articles from reputed high impact factor journals from IEEE, Springer and Elsevier publishers. The data was collected from K.S. Hegde Medical Academy, Mangalore. Researchers have built an expert system prototype model to predict the difficulty in airway management. This paper discussed the implementation of fuzzy rule base model using Intel Distributed Python package.

Authors have experimented with four algorithms and would like to experiment with more algorithms to fine tune the rule base, data to get better results and accuracy.

Limitations and Future Work

Authors are collaborating with doctors in KS Hegde Medical Academy to collect more real data on day to basis from patients and implement this prototype in this hospital on day to day basis. Authors are designing a website, apps for doctors and hospital to share patient's data to build standard database for airway management. In future this website will facilitate doctors to share airway management experiences with each other case by case to enhance the skill of novice doctors.

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