

# ARTIFICIAL INTELLIGENCE IN PAEDIATRIC ANAESTHESIA

## Abstract

Artificial intelligence (AI) is currently the buzz word in health care and perioperative medicine. This chapter gives a brief outline of the various applications of AI in Paediatric Anaesthesia. Starting with understanding some basic concepts and terminology used in AI, it goes on to describe the advantage of machine learning and AI in anaesthesia. The scope of AI in various stages of our anaesthesia practice beginning from preoperative assessment, intraoperative management and post operative care, to predicting perioperative outcomes, guiding transfusion protocols and understanding pain in children has been explored. Other ancillary uses of AI such as paediatric critical care, clinical decision support systems, operating room logistics, education and skill development etc have also been investigated. Finally, it lays out the limitations of AI in anaesthesia practice.

**Key words:** Artificial intelligence, machine learning, paediatric anaesthesia.

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## I. INTRODUCTION

Since the time, humans evolved and developed over time, the one thing which characterized us and made us distinctive and exclusive was our unique and highly complex organ called the brain and its component called intelligence. Intelligence is the burgeoning hot topic of discussion today. The basic definition of Intelligence is the ability to understand, learn and think. Human intelligence is a mental quality that consists of the abilities to learn from experience, adapt to new situations, understand and handle abstract concepts, and use knowledge to manipulate one's environment. Once these were explored, achieved and fulfilled in all spheres of life, humans progressed one step further towards simulating human intelligence using machines and computers. AI programming essentially focuses on cognitive skills including learning, reasoning, self correction and creativity. It mainly involves acquiring data, forming rules in the form of algorithms, choosing the right algorithm to fulfil a desired action, fine tuning algorithms and finally using various techniques to develop novel ways of achieving something.

It all began from 1950 when Alan Turing, the father of AI, came up with his Turing test, which was based on the fact that computers can simulate cognitive human actions. The term AI was first purported by John McCarthy in 1956 as the science and engineering of making intelligent machines. After its initial applications in various fields like business, education and marketing to automate repetitive and detail oriented human tasks, it has also infiltrated the field of medicine. The concept spread further on when finally in 2016, a significant proportion of investment was directed towards AI in health care.

In medicine, AI has been divaricated into two branches - One dealing with applications in record keeping systems and data handling and the other dealing with robots and automated machines performing procedures including surgeries. Anaesthesia as a speciality has been the frontrunner of technological advancements right from the time ether was introduced by Morton in 1846. So, it comes as no surprise that we are on a quest now to use AI technology to make anaesthesia safe, accurate and tailor-made for each patient.

## II. UNDERSTANDING THE BASICS OF AI

When we think AI, our mind is automatically drawn to the image of a robot. Robotics is an essential component of AI, but it is important to understand the other aspects of AI namely, machine learning (ML) and natural language processing (NLP). Robotic systems in anaesthesia are classified as either pharmacological robots that are the basis of the closed-loop anaesthesia delivery system (CLAD) or mechanical robots that some authors propose can be used to perform actions that need precision and dexterity like intubation and peripheral nerve blocks.<sup>1,2,3,4</sup> NLP is the technology used by machines to understand human language. Siri and Alexa are examples of application of NLP. Machine learning (ML) is an exciting subset of AI that enables machines to analyse data by using algorithms and then make predictions or decisions based on this analysis. In ML language the data that is analysed is called the input or independent variable and what the machine predicts after analysing the input data is called the output or dependant variable. Unlike in statistical models, the machine tries to find complex nonlinear relationship between the dependent and independent variables.

ML can be supervised, unsupervised or reinforced. In supervised learning, the machine is trained using a well labelled dataset. For example, data containing photographs of men with difficult airway. Now the input data is randomly divided into two- the training data set and the test dataset. The computer first analyses the training data (photographs) using an algorithm which it tests repeatedly to find an association between input and the desired output (difficult airway in this case). Once this is done, this algorithm is applied on the test dataset to see if it can accurately predict the desired outcome (to analyse the photographs to predict if it is a difficult airway). In unsupervised learning, the data is unlabelled. The computer tries to find patterns and associations between variables within a dataset which can be used in new ways to classify patients. An example would be if the data contains photographs of both men and women and the computer applies its logic to differentiate between the two genders. Reinforcement learning refers to a process by which an algorithm is made to attempt a certain task and then learn to perform the task accurately based on feedback. An example would be a machine that controls propofol infusion rates using BIS and MAP values of patients <sup>5</sup>. The task here is propofol infusion and the feedback is the depth of anaesthesia as measured by BIS and MAP, which the machine uses to titrate the ongoing doses of propofol.

Deep learning is a subset of ML that develops algorithms using artificial neural networks which have three or more layers which are interconnected. These neural networks are made as an attempt to behave like the human brain to process large amount of data. The data here is first passed forward through each layer where it is analysed and additional points for prediction and categorisation of the data is added at each layer to make the process more accurate. This whole process is repeated backwards to adjust for any errors that could have occurred during the initial processing in the earlier layers. This backward and forward processing of data makes the system more accurate at predicting outcomes. Face identification feature in an iPhone is made possible through deep learning. When you present your face to the phone the first time, the image of your face is processed through multiple layers that try to identify features of your image to the minutest of details. This process is repeated forward and backward to make the process of recognising your face more and more accurate. Once this is registered, every time you present your face to the phone it recognises the image and unlocks the phone.

There are numerous other terms that are used in AI, but we have discussed only the basic terminology that is needed to understand the prospective use of AI in paediatric anaesthesia.

### **III. ADVANTAGE OF AI AND MACHINE LEARNING IN ANAESTHESIA**

Traditionally in medicine we have relied on statistics to find the relation between a disease cause and outcome. But standard statistics can only find linear relationships between the available data. For example, cigarette smoking causes lung cancer. In addition, statistics is also subject to the element of bias. Machine learning on the other hand can identify nonlinear relationship (factors that we dint know could influence the outcome) between variables in the dataset provided without adding bias. Machine learning techniques are, therefore, more suited to solving the complex and fast evolving problems we deal with in medicine and in particular, anaesthesia. In the fields of radiology and pathology for example, machine learning algorithms have been reported to be comparable in classifying images and identifying pathologies at a rate similar to an expert radiologist or pathologist respectively<sup>6,7,8,9</sup>. Machine

learning will therefore be a value addition in improving the standards of clinical judgement and existing standard-of-care, to enhance clinical outcomes in the peri operative patient population.

#### IV. SCOPE OF AI AND MACHINE LEARNING IN ANAESTHESIA

**1. Preoperative Risk Assessment:** A thorough preoperative assessment is the first step in the anaesthesia preparation of a patient<sup>10</sup>. The American Society of Anaesthesiologists' Physical Status (ASA-PS) score is universally used to assess the patient fitness for surgery in all patient populations, with higher scores being associated with increased risk of morbidity and mortality. Machine learning techniques have been used to assign ASA-PS scores in the adult population, but some researchers have reported poor performance of these algorithms in identifying ASA-PS 4 category in adults. A reason for this could be the wide variability in the method of obtaining and reporting medical history of the patients which makes it difficult to standardize data<sup>11-14</sup>. Risk assessment in children is often more difficult due to their varied physiology ranging from prematurity to young adulthood. Machine learning provides an opportunity to develop new risk assessment tools that can be tailor made to each paediatric age group<sup>15</sup>.

**2. Anaesthesia Procedures:** As anaesthesiologists we routinely perform procedures such as intubation, vascular access, regional block etc using video-based systems or ultrasonography. There have been several reports of the use of machine learning in image processing relevant to anaesthesia procedures. Some of the opportunities for the use of machine learning in paediatric anaesthesia practice are as follows:

- **Airway Management:** The evaluation and management of difficult airway is a basic and vital skill for any anaesthesiologist. Mallampati score used for assessment of airway in adults is practically difficult to use in the paediatric age group. Machine learning algorithms have been used to predict difficult airway by 2-D face image analysis that can extract morphological traits associated with a difficult airway. This would be especially beneficial in the paediatric population<sup>16</sup>. Specialised robots are being created to perform intubations. Neural networks can be used to provide a "GPS like guide during FOB and video laryngoscopy to prompt the anaesthesiologist's real time location inside the airway.<sup>17</sup> Machine learning algorithms have been developed that are able to detect oesophageal intubations in anaesthetised adults from the ventilatory waveforms<sup>18,19</sup>. ML algorithms can be used to recognise patterns that could be early warning signs of critical respiratory events<sup>20</sup>. Knorr and colleagues<sup>21</sup> used a photoplethysmography based neural network to identify airway obstruction in patients in the PACU. The scope of AI in paediatric airway management is therefore numerous. This will help us anaesthesiologist to safely manage the difficult airway in babies.
- **Ultrasound-Based Procedures:** We use ultrasound guidance for procedures such as nerve blocks, central neuraxial blocks and vascular access, which improves the safety and accuracy of these procedures. But identifying the Sono anatomy of these structures requires frequent use of this technology<sup>22</sup>. Machine learning algorithms could be used to enhance the visualisation of these anatomic structures which is of potential advantage especially in the paediatric population. But development of this

technology in children needs further research which will also take into consideration the age-related changes in anatomy especially of the central neuraxial structures<sup>23</sup>.

- **Depth of Anaesthesia Monitoring:** More recently artificial intelligence and neural networks have been used to improve depth of anaesthesia monitoring to prevent awareness under anaesthesia. While majority of the research focussed on the use of BIS and electroencephalography to assess anaesthesia depth, others have included MAP, heart rate variability and even mid latency auditory evoked potential to differentiate between the awake and anaesthetised state<sup>24,25</sup>
- **Control of Anaesthesia Delivery:** Different closed loop systems are now in use in our operating rooms for automated delivery of anaesthetic agents. Some of these systems use reinforcement learning, where feedback given by BIS or NMT monitor will regulate the delivery of anaesthetic and neuromuscular blocking agents. This helps titrate anaesthetic drug doses to meet the real time requirement in the anaesthetised patient. Neural networks have also been used to predict the rate of return of consciousness from anaesthesia, the recovery from neuromuscular blockade and hypotension post induction and spinal anaesthesia which can help titrate the drug doses at the end of surgery and at induction of anaesthesia<sup>26,27,28</sup>.
- **Perioperative Transfusion Guide:** Development of machine learning models that will accurately predict perioperative bleeding risk in children especially neonates will help in perioperative decision making, planning blood conservation strategies and use of antifibrinolytics, reducing delays in procuring blood and avoiding unnecessary transfusion in low-risk patients. Machine learning in predicting complications following blood transfusion can be similarly used to predict patients at increased risk of serious complications from blood transfusion, transfusion related lung injury and transfusion associated circulatory overload<sup>24</sup>. This can help guide the perioperative physician in taking informed decisions regarding blood transfusion.
- **Prediction of perioperative outcomes:** Critical airway events such as bronchospasm, laryngospasm and O<sub>2</sub> desaturation are common in the paediatric population. The incidence is greater in the younger age group and the common risk factors predisposing to such events are known to us. If data regarding these risk factors and the airway outcomes is collected, then we could use AI algorithms to accurately predict children who are at risk of adverse airway outcomes. Lundberg and colleagues<sup>29</sup> developed a ML system that not only predicted hypoxemia but also explained the risk factors. Kuo and colleagues used an artificial neural network in the ICU setting for predicting weaning outcomes. We could use a similar algorithm to predict successful extubation of paediatric patients after general anaesthesia.<sup>30</sup>
- **Pain management:** Researchers are trying to use machine learning to help understand pain. Machine learning analysis of whole brain scans<sup>31</sup>, photoplethysmograms and skin conductance<sup>32</sup> waveforms are some of the many methods used to identify pain in adult patients. This in turn has been used to identify patients who are at risk of developing chronic pain and who might benefit from preoperative consultation with a pain physician or the acute pain service. This will help plan perioperative pain management including opioid dosing in such patients.

Identification of pain in the very young child is usually tricky since we must rely on non-verbal clues and the use of machine learning techniques to identify pain in this patient population will be beneficial.

- **Machine Learning in Paediatric critical care:** The paediatric ICU is a store house of patient related information and data and has hence become an area of focus for machine learning in paediatrics. Some of the applications of AI in the critical care setting under study are prediction of mortality by analysing electroencephalogram data<sup>33</sup>, use of Paediatric Early Warning Score (PEWS) to predict the need for ICU admission in hospitalised children<sup>34</sup> and identifying critically ill children who are at high risk of progressing to cardiac arrest<sup>35</sup>. Machine learning algorithms have also been used to predict the risk of development of sepsis<sup>36</sup>, for early prediction of AKI<sup>37</sup> and to predict long term neurologic outcomes in children with traumatic brain injury<sup>38</sup>.

The application of machine learning in the perioperative period is rapidly evolving. In addition to its wide range of clinical application, machine algorithms are now being used to improve operating room logistics<sup>24</sup> like scheduling, staffing, discharge from PACU etc. Another application of machine learning algorithms is as a clinical decision support system which include medication interaction alerts to patient safety reminders<sup>39</sup>. All these help in improving the quality of care, patient safety and the ultimately the perioperative clinical outcomes of the surgical population.

## V. LIMITATIONS OF AI APPLICATION IN ANAESTHESIA

Once we understand the basics of machine learning, it is easy to see that for building an AI algorithm that is accurate, reproducible, and safe to use in any given clinical scenario, the data used to train it should be of high quality and free from bias. A term that commonly appears in AI discussions is overfitting. Overfitting typically occurs when a machine learning model becomes so familiar with the training data that it fails to predict outcomes in a new set of data<sup>41,42</sup>. For example, if the data on difficult airway patients consist only of photographs of men, then the AI model may fail to accurately recognise features of difficult airway women because in the training set it has identified predictors of difficult airway only in males. Over fitting occurs when the sample size of the data is too small, or if it has a lot of irrelevant information (called noisy data)<sup>42</sup>. It is important therefore to collect as much data as possible to avoid such bias. The collection of large data bases leads to another key issue in AI which is data ethics and data security<sup>1</sup>. Informed consent, patient privacy, security, data protection are all important aspects of AI that need to be investigated and legislature pertaining to these must be put into place. Another factor that may act as barrier for use of AI in clinical anaesthesia is the concern that someday machines may overpower and replace humans. Matthias Görge and Mark Ansermino bring in an interesting terminology called “augmented intelligence”, to describe AI. Since it is essentially the integration of traditional statistical methods with machine learning, AI can empower anaesthesiologists to make proactive decisions in varied clinical contexts, making the operating room environment safe for the patients<sup>43</sup>.

## VI. CONCLUSION

Right from performing mundane tasks like turning on lights in our homes or calling a friend in our contact list by voice command to putting space scientists up on the moon; computers have slowly but surely invaded all aspects of human life. It's not surprising then that healthcare and anaesthesia have not been left untouched by it. Where we humans can take informed decisions based on our comprehensive understanding of scientific phenomena, artificial intelligence can only make predictions based on the data it has reviewed and analysed<sup>44</sup>. Current research on use of AI in anaesthesia is focused mostly on the adult population. It will help if clinicians who are in the front-line can closely collaborate with computer scientists, database architects and data managers to explore the vast opportunities that AI offers to advance care in the specialty of paediatric anaesthesia<sup>1</sup>.

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