Machine Learning As Our Weapon to Become Anesthesiologist 5.0

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ABSTRACT

Machine learning is one of the most renowned things that have emerged in the last five years in medicine. The machine is made as if it has the cognitive ability to think independently, is able to distinguish incoming inputs and get the desired output. Along with the development of statistical and computer science, machine learning has evolved into a distinct subfield within the broader domain of data science, with far-reaching implications for various sectors, including healthcare. In medical science, technology and artificial intelligence are starting to take over anesthetic services. This paradigm shift necessitates a fundamental change in the role of future anesthesiologists A future anesthesiologist will need to continuously monitor and evaluate the performance of data science and artificial intelligence systems, and make adjustments when necessary to improve impact on patient care and outcomes. Anesthesiologists of the future will need to harness the power of data science and artificial intelligence to enhance patient care continually, emphasizing adaptability and collaboration as key elements in delivering improved healthcare outcomes.

Keywords: anesthetic services; artificial intelligence; cognitive ability; machine learning

Machine Learning Sebagai Senjata Untuk Menjadi Ahli Anestesi 5.0

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ABSTRAK

"Machine learning" merupakan salah satu hal paling terkenal yang muncul dalam lima tahun terakhir di dunia kedokteran. Mesin dibuat seolah-olah memiliki kemampuan kognitif untuk berpikir mandiri, mampu membedakan input yang masuk dan mendapatkan output yang diinginkan. Seiring dengan perkembangan ilmu statistik dan komputer, pembelajaran mesin telah berkembang menjadi subbidang tersendiri dalam domain ilmu data yang lebih luas, dengan implikasi yang luas bagi berbagai sektor, termasuk layanan kesehatan. Pergeseran paradigma ini memerlukan perubahan mendasar dalam peran ahli anestesi di masa depan Seorang ahli anestesi di masa depan perlu terus memantau dan mengevaluasi kinerja ilmu data dan sistem kecerdasan buatan, dan melakukan penyesuaian bila diperlukan untuk meningkatkan dampak pada perawatan dan hasil pasien. masa depan perlu memanfaatkan kekuatan ilmu data dan kecerdasan buatan untuk terus meningkatkan layanan pasien, menekankan kemampuan beradaptasi dan kolaborasi sebagai elemen kunci dalam memberikan hasil layanan kesehatan yang lebih baik

Kata Kunci: *artificial intelligence; kemampuan kognitif; machine learning; pelayanan anestesi*

INTRODUCTION

Machine learning is one of the hottest things that have emerged in the last five years in medicine. The trend towards machine learning has only emerged in the last two years, allegedly due to COVID-19 pandemic. Excellence in data processing speed, minimum direct contact on subjects and the extrapolating ability are tantalizing processes of machine learning.

It turns out that since 2007 an idea has been put forward for a new paradigm in which self-learning machine on existing data patterns would make it easier for users compared to conventional learning. In this review, we want to summarize the development of machine learning especially in Intensive Care Unit (ICU) to assist future anesthesiologist.

The machine is designed as if it possesses the cognitive ability to think independently, distinguish incoming inputs, and update its own system to achieve the desired output (Table 1). Alongside the advancements in statistical and computer science, the cognitive learning abilities of machines have been increasingly refined, evolving into a subfield of data science known as machine learning (Fig.1).

Tabel 1. Classical approach and cognitive perspective of intelligent system[1]

Comparative between classical approach of intelligent systems and the cognitive perspective	
Classical paradigm	**Cognitive perspective**
Centered on the programmer	Centered on the system
The programmer possess the knowledge	The system discovers and build the knowledge
The programmer provides the resources	The system finds the resources
Off-line learning	On-line learning
The programmer "teaches" the system	The system learns by itself
Learning process is limited and isolated	Learning process is continuous and contextual
The system carries programmer's vision	The system develops its own "self"

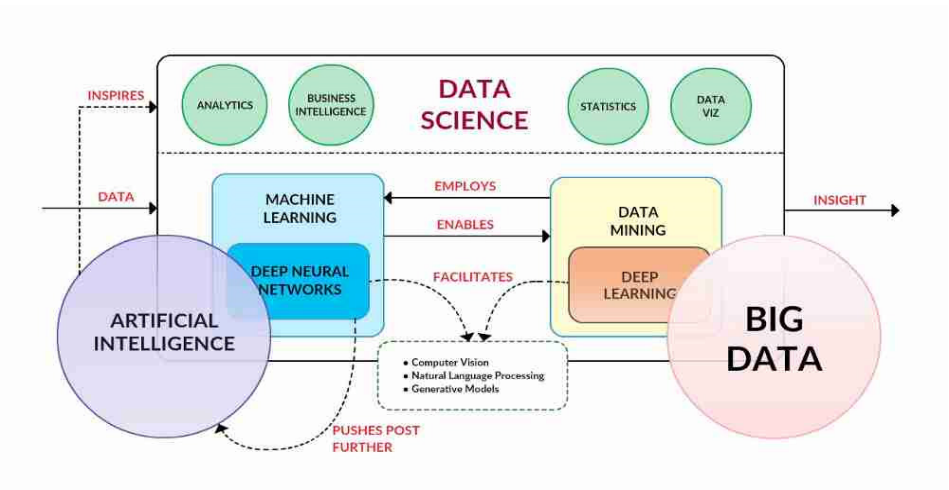

Figure 1. Relationship between Artificial Intelligence and Big Data[2]

As part of artificial intelligence, which is based on the formation of the human brain's mindset, much of the human brain relies on pattern recognition. However, humans have limited memory capacity; therefore, machine learning takes the form of an algorithm-based learning pattern. This pattern then develops in such a way that it can provide predictions from large data sets. Figure 2 attempts to explain the relationship between big data and the role of artificial intelligence in unlocking the deep potential of machine learning. Machine learning can explore the potential for improved data prediction and analysis according to specific goals.

Machine learning can be divided into two main types, namely supervised and unsupervised

machine learning (Fig. 2). Unsupervised machine learning techniques have been employed to explore massive amounts of data encoded in electronic medical records, such as patient charts and cost-effectiveness, while supervised machine learning algorithms offer advantages in automated pattern recognition, particularly in image analysis, such as radiology images.

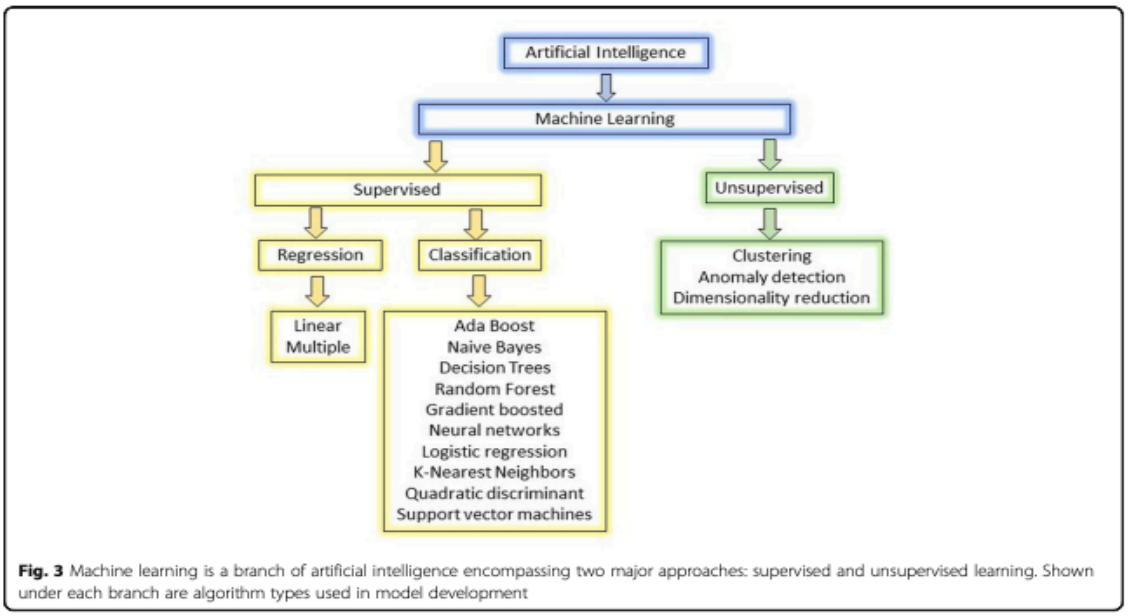

Fig. 3 Machine learning is a branch of artificial intelligence encompassing two major approaches: supervised and unsupervised learning. Shown under each branch are algorithm types used in model development

Figure 2. Categories of machine learning[3]

Machine learning appears to be increasingly utilized in the intensive care sector, as evidenced by numerous studies employing multiple datasets. For example, the Houthooft study utilized datasets from patients to forecast patient survival and length of stay.[4] On the other hand, Awad et al. applied several machine learning algorithms to the Multiparameter Intelligent Monitoring in Intensive Care (MIMIC)-II data in order to predict ICU mortality.[5] Yoon *et al*. developed a method to predict instability in the ICU based on logistic regression and random forest models of electrocardiogram (ECG) measures of tachycardia. Other studies have also been published describing the use of machine learning models in generating patient-specific risk scores for pulmonary emboli, prediction of acute kidney injury, volume responsiveness after fluid administration, and many more.

There has been considerable interest also in detecting patient-ventilator asynchrony. Chen et al. developed an algorithm to identify ineffective efforts from the maximum deflection of the expiratory portion of airway pressure and flow.7 An algorithm developed by Blanch et al. compared a theoretical exponential expiratory flow curve to actual flow tracings.[8] In the other hand, Rhem *et al*. and Adams *et al*. developed a set of algorithms to detect two types of asynchrony associated with dynamic hyperinflation, double triggering, and flow asynchrony.[9,10] While in other study, Sottile et al. evaluated several types of machine learning algorithms, including random forest, naïve Bayes, and AdaBoost on data recorded from 62 mechanically ventilated patients with or at risk of acute respiratory distress syndrome (ARDS).[11]

In the perioperative field, Hatib *et al*. applied machine learning to hundreds of thousands of waveform recordings in surgical patients or critical care units to construct a hypotension prediction index (HPI) ranging from 1 to 100. The prediction system then has been commercialized, and the IOH (Intra Operative Hypotension) alarm is activated when the HPI reaches likelihood equal to or greater than 85%. This value is accompanied on the screen by other hemodynamic variables that can guide therapeutic decision according to the possible origin of IOH.[12]

Betts *et al*. used machine learning from collected health administrative data to determine women`s

risk of common post-partum complication leading to hospital admission. They found that information could be presented to clinical staff after delivery to help guide immediate postpartum care, delayed discharge, and post-discharge patient follow up.[13]

Meanwhile Westcott *et al*. used supervised learning with regression, tree, and kernel-based machine learning methods to create classification models. Machine learning methods can be used to identify women at risk for postpartum hemorrhage who may benefit from individualized preventative measures. Models stratified by mode of delivery, proven to be excellent discrimination but lacked the sensitivity necessary for clinical applicability. An unbiased approach to hemorrhage risk prediction may be superior to human risk assessment and represents an area for future research.[14]

Although, it sounded promising, there were several drawbacks of these researches. These researches usually set up in a retrospective design because amount of sample needed in order to get a high accuracy is huge. Therefore, there was risk of bias especially in inputting the data in medical records. Beside finding the accuracy using the area under curve (AUC) analysis, some of these studies did not use other model of analysis to minimize the potential of underfitting and overfitting. Underfitting and overfitting happened if the data was too simple or too complex. This problem also become a challenge for further studies to make a model fitted study.

Due to major changes in medicine where technology and artificial intelligence are starting to be utilized in many areas of anesthesia-related patient care, it is urgently necessary to propose an additional competency in understanding data science research for an anesthesiologist. The roles of the competency included to identify areas in the anesthetic field where data science and artificial intelligence are of great benefit, such as patient monitoring, drug dosing, or risk prediction. To establish a framework for data collection, storage and analysis, ensure all data is managed safely and legally blinded. Last but not least, to collaborate with other departments or institutions to share knowledge and resources on research projects. Beside if the sophisticated program, a future anesthesiologist 5.0 still need to continuously monitor and evaluate the performance of data science and artificial intelligence systems, and make structural and process adjustments when necessary to improve impact on patient care and outcomes.

CONCLUSION

We conclude that in medical science, technology and artificial intelligence are starting to take over anesthetic services. Due to major changes in medicine in which technology and artificial intelligence are starting to take over anesthetic services, it is urgently necessary to propose an additional competency activity in data science for an anesthesiologist. A future anesthesiologist will need to continuously monitor and evaluate the performance of data science and artificial intelligence systems, and make structural and process adjustments when necessary to improve impact on patient care and outcomes.

CONFLICT OF INTEREST

There is no conflict of interest in this article text

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