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On the Horizon: Specific Applications of Automation and Artificial Intelligence in Anesthesiology

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Abstract

Purpose of Review—The purpose of this review is to summarize the current research and critically examine artificial intelligence (AI) technologies and their applicability to the daily practice of anesthesiologists.

Recent Findings—Novel AI tools are developed using data from electronic health records, imaging, waveforms, clinical notes, and wearables. These tools can accurately predict the perioperative risk for adverse outcomes, the need for blood transfusion, and the risk of difficult intubation. Intraoperatively, AI models can assist with technical skill augmentation, patient monitoring, and management. Postoperatively, AI technology can aid in preventing complications and discharge planning. While further prospective validation is needed, these early applications demonstrate promise in every area of perioperative care.

Summary—The practice of anesthesiology is at a precipice fueled by technological innovation. The clinical AI implementation would enable personalized and safer patient care by offering actionable insights from the wealth of perioperative data.

Keywords

Artificial intelligence; Automation; Artificial neural networks; Deep learning; Anesthesiology; Perioperative medicine

Introduction

Anesthesiologists have embraced innovation throughout the history of anesthesiology. From the first use of ether in 1846 to the present, our specialty has implemented novel technologies and medications to set new standards with the goal of improving patient safety and care delivery [1]. Artificial intelligence (AI) technologies are an area of heavy research as a new frontier in medicine [2]. These technologies have attracted significant investments —the global AI in healthcare market size in 2022 was $15.4 billion and is projected to grow to $208.2 billion in the next 7 years [3]. In 2022, 90 new AI-integrated medical devices were approved by the Food and Drug Administration (FDA) [4]. Table 1 shows a breakdown of

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AI-enabled medical devices currently on the market by specialty. The paucity of approved anesthetic devices on the market and the extensive research in this field herald an impending new age of AI in anesthetic care.

This opportunity for innovation using AI has applications for each phase of perioperative care: from perioperative risk prediction, transfusion needs evaluation, technical skills augmentation, patient monitoring and management, and discharge planning (Fig. 1). We present studies using AI, defined as a computer algorithm able to synthesize, infer, and perceive information in a fashion similar to human intelligence, and machine learning (ML), defined as a type of AI algorithm able to generate insights from data without explicit programming. The purpose of this narrative review is to present the most recent specific applications of AI or ML for the anesthesiologist and critically assess the opportunities and limitations that this new technology can bring for the safety and efficiency of patient care.

Search Methodology

We searched Pubmed and Web of Science databases for articles published between 2019 and 2022. The following terms were used in combinations: “anesthesiology”, “preoperative”, “intraoperative”, “postoperative” and “artificial intelligence”, “machine learning”, “AI”, “automation”. A glossary of the commonly used terms is presented in Table 2; most methods in the field of AI are explained in detail [5].

AI Technologies to Predict Perioperative Risk

The goal of preoperative assessment is to detect and optimize patient risk factors to achieve the best perioperative outcome. The American Society of Anesthesiologists (ASA) classification system is the most commonly used system to categorize patients and provide a qualitative measure of their perioperative risk of receiving anesthesia based on their comorbidities [6]. The ubiquity of this scoring system likely originates from its ease of use; however, weak inter-rater reliability at all stages presents an opportunity for improvement [7, 8]. Additionally, the lack of personalization means that obstetric, pediatric, and adult surgical comorbidities are not differentiated, adding to the subjective bias which limits the accuracy of this scoring system [7].

ML models can provide accurate predictions of perioperative risk. ML techniques allow for the analysis of diverse patient data such as demographics, comorbidities, laboratory results, and even free text from the clinical notes and scheduling records; thus, these models are ideally suited to integrate large amounts of perioperative patient data. There are numerous sources of patient data available for the creation of these models; the most used are large administrative databases and electronic health records (EHR) [9•, 10•]. In addition, an excellent review of the methodology for the development and validation of clinical predictive models was recently published [11]. A large study using the American College of Surgeons National Surgical Quality Improvement Program database, which collects data from 722 hospitals from 15 countries, was used to develop highly accurate neural network models to predict postoperative morbidity and mortality [12••]. The approach of using neural networks, a type of ML model that uses computer networks similar to the ones in the human brain that can process information to gain insights from it, allows for accurate predictions; however, a relative disadvantage of those types of models is the lack of transparency into the generation of the model output. The study involved the development of three machine learning models which used data from more than 5 million patients using 48–76 input features and performed with an area under the curve (AUC) of 0.84–0.88. Another model based on claims data achieved similar predictive power for 30-day mortality and 23 adverse outcomes [13]. These results are robust and promising as the models were developed following established guidelines and outperformed widely used surgical risk calculators; in addition, the excellent external validation suggests these models may apply to a wide range of patient populations. A major limitation of the claims-based model is the lack of detailed patient data, such as comorbidities, lifestyle, and pharmacological data.

Developing models based on EHR data allows for the inclusion of vast data collected from multiple clinical encounters, laboratory tests, imaging, and vital signs. In a study of 276,341 patients presenting for non-cardiac surgery, using preoperative data, an xgboost model was able to accurately predict the 30-day mortality risk with an AUC of 0.96 [14]. The results were validated in an external dataset of 63,384 patients. An added benefit of the methodology was the utilization of explainable ML methods, which can demonstrate the patient factors that contributed to the predictions. Xue et al. also trained a machine learning algorithm on a dataset of 111,888 patients and predicted postoperative risk of acute kidney injury, deep vein thrombosis, pulmonary embolism, and pneumonia; the model achieved good performance [15]. Depending on the model design and the patient risk factors included, adding text features extracted from the preoperative surgical scheduling may improve predictions [16], while adding intraoperative data may not improve the predictions, especially if the performance is already excellent [17]. Models like these can be integrated into the EHR so that all input patient factors are ingested automatically, and the patient's personalized risk of morbidity and mortality is available at the preoperative visit. In this way, the anesthesiologist may identify modifiable risk factors which can be addressed in a timely fashion.

The preoperative evaluation can also be streamlined. Using natural language processing (NLP), tools that allow machines to process and understand human-generated text, relevant data can be efficiently extracted from patient history. Using data from 93 patients and their 9765 clinical notes, an NLP model was able to extract information relevant to the preoperative evaluation [18••]. Compared with the data extracted by an experienced anesthesiologist, both the model and the clinician agreed in 80.2%; additional information missed by the anesthesiologist was identified by the model in 16.6% of the instances, while the model missed only 2.2% of the instances identified by the anesthesiologists. This pilot study was focused only on clinical notes and did not integrate laboratory results, vital signs, or medication; however, it highlights the potential of this approach to save valuable clinician time, on average, 15 min per patient. Integrating models such as those in the preoperative evaluation may improve the accuracy of preoperative assessment and potentially prevent human errors or suggest the need for further evaluation.

Perioperative Risk of Transfusion and Blood Management

Multiple ML models have been aimed at accurately predicting blood transfusion needs preoperatively. Implementing those in clinical practice would allow preparation for high-risk individuals while conserving resources for those at low risk. Using data from over 2 million patients, an xgboost model was developed to predict the occurrence of perioperative blood transfusion [19••]. The traditional approach of estimating blood transfusion risk is based only on procedure-specific factors; the new model outperformed the standard of care by also incorporating patient-specific factors. The most important variables for model prediction included procedure-specific transfusion rate, preoperative hematocrit, age, and laboratory indicators of coagulopathy. The large dataset and model design allowed the generalization of the predictions across hospitals that may have varying transfusion practices by specifying the local procedure-specific risk of transfusion. When validated using a single academic center's data, the model reduced the number of recommended type and screen orders by 15% while maintaining 96% sensitivity. While further work in implementing and prospectively evaluating this model is needed, well-designed studies such as this one are an important first phase.

Subsequently, predicting the need for and the amount of intraoperative transfusion is a more complex task due to the multiple patient- surgeon-, and institution-specific factors involved. A pilot study developed an algorithm that accurately predicted intraoperative RBC transfusion amounts of 0, 1–3, and more than 4 units for patients undergoing cardiothoracic surgery [20]. The model used retrospective data available preoperatively from 2847 patients and achieved high predictive power. One concern, especially in models developed using data from a single institution, is that these models will perpetuate current practice. If there is a change in the institutional guidelines, for example, introducing a more conservative transfusion approach, those models would no longer be current and may need to be redesigned. Therefore, implementing those models would require monitoring of the performance and evaluation of the clinical needs. The most benefit would be derived from systems that automatically alert anesthesiologists and blood bank personnel to ensure appropriate preparedness and blood product allocation in patients at high risk. Combining pre- and intraoperative data in real time can improve the accuracy of predictions. Indeed, a massive transfusion model achieved an AUC of 0.96 and had excellent performance during external validation [21•]. Models like these would help direct the physician's attention to early changes in the patient's condition and timely intervention so that the risks of bleeding are decreased.

Prediction and Management of Difficult Airway

Predicting difficult intubation, the leading cause of anesthesia-related mortality, is traditionally based on physical examination and evaluation of thyromental distance and Mallampati score; however, this method may fail to identify up to 93% of the cases of difficult intubation [22]. ML models using demographic and clinical information can perform well, as demonstrated by a small study in 500 patients scheduled for thyroid surgery [23]. These early results will need to be validated further in larger and more diverse patient populations. As physicians evaluate multiple other facial features, machine learning analysis to extract features from face images may be used to predict difficult to intubate patients [24, 25]. A recent pilot study using only frontal face images developed an ML model that predicted difficult intubation with better accuracy than the conventional bedside evaluation [26•]. While image analysis may have the potential to outperform certain aspects of the physical exam, it would require the additional step of obtaining standardized facial photographs of patients subject to variability in lighting and patient facial features. A potential further investigation should include the combined use of physical examination and image analysis, and the utility of this approach should be evaluated prospectively.

Intraoperatively, AI tools can augment the skills of the anesthesiologist during challenging intubations. Matava et al. created a highly accurate tool able to identify the vocal cords and tracheal rings using 775 videos of video laryngoscopy and bronchoscopy [27]. The best-performing algorithm achieved a specificity of 0.98 and a sensitivity of 0.86 in processing simulated live video to identify airway anatomy. Subsequently, AI tools like this one can be used to supplement the clinician's skills. For example, an AI-assisted system allowed up to 21% increased accuracy in recognizing airway anatomy during bronchoscopy for specialists and novice physicians [28]. Zhao et al. applied a similar concept to the intubation of neonates. The neural network model automatically provides real-time feedback to pediatric trainees on the success of their neonatal intubation with an average classification accuracy of 92% [29]. These examples indicate how software could be used to provide real-time feedback for practitioners performing procedures or learning to do them.

AI-Assisted Regional Anesthesia

AI technologies can augment anesthesiologists' technical skills and are increasingly being adopted in ultrasound image acquisition and interpretation, which are the cornerstones of regional anesthesia techniques. In December 2022, the FDA authorized a new AI software, ScanNav, which can place color overlays of key anatomical structures on real-time ultrasound images to aid in the placement of regional anesthesia [30]. Using this AI-assisted technology, 21 non-expert anesthesiologists achieved correct block view in 90.3% and correct image identification in 88.8% of the scans, which was an 11–15% improvement compared to scans without the device [31•]. Tanwani et al. describe an augmented reality system, HoloLens, which displays an ultrasound transducer marker that projects a needle's trajectory for use in neuraxial anesthesia placement [31•]. The clinical utility of this needle-guidance system will need to be established. The field of augmented reality and the application of software-based AI tools demonstrate the potential of the technology in improving skill-based procedural tasks.

Intraoperative Hypotension Prediction

Intraoperative hypotension, specifically mean arterial pressure (MAP) < 60–70 mmHg, has been associated with adverse patient outcomes, including acute kidney injury, myocardial injury, and heightened 30-day mortality [32]. Multiple machine learning models to predict intraoperative hypotension have been developed. Most of these models utilize routinely collected biosignal data and predict the incidence of hypotension in the next 5–15 min [33, 34]. The first model, the hypotension prediction index, HPI, was developed using arterial waveform features and is integrated into a commercially available device [35]. To date, multiple studies have demonstrated prediction accuracy of a hypotensive event 5–15 min before it occurs, even in patient populations different from the ones from which the model was developed [36•, 37].

Recent work by Lee et al. demonstrates the viability of such tools. In a retrospective observational study of 3301 patients, a deep learning algorithm was designed to predict intraoperative hypotensive events defined as a MAP < 65 mmHg [33]. The algorithm was developed using intraoperative waveform data, including arterial line pressure tracings, electrocardiography, photoplethysmography, and capnography, to identify the likelihood of a hypotensive event and predict future MAP. With a prediction horizon of 5 min in the future, the best-performing algorithm had an AUC of 0.93 and a sensitivity of 85% for the prediction of a hypotensive event. As these models were developed using data from patients presenting for different types of surgery in a single tertiary care center, there is a possibility of selection bias, and the external validity of these results has not been verified. In addition, data about the clinical context in which the hypotensive events occurred was not available, which may limit the application of this tool. Despite these limitations, identifying patients at risk for intraoperative hypotension would allow better monitoring and prevention of hemodynamic instability.

Identifying the etiology of intraoperative hypotension may be challenging in clinical care, especially when multiple mechanisms may be contributing. A secondary analysis of prospectively collected hemodynamic data from 82 patients presenting for major abdominal surgery collected using arterial line and invasive pulse wave analysis investigated the different endotypes associated with hypotension [38•]. Using data from 615 episodes of intraoperative hypotension, six endotypes were identified, including myocardial depression, bradycardia, vasodilation with and without cardiac index increase, hypovolemia, and mixed type. Studies such as this one demonstrate the potential of machine learning methods to aid the causal treatment of intraoperative hypotension.

Intraoperative Fluid and Blood Pressure Management

Individualized blood pressure management strategy to maintain the SBP above 10% of the preoperative values has been associated with better postoperative outcomes, including reduced risk of postoperative organ dysfunction [39]. The value of closed-loop control and target-controlled infusion systems to achieve optimal blood pressure control has been demonstrated in research since the 1950s; however, the clinical use of these devices is limited in the USA [40]. These algorithms use pharmacologic principles to titrate drug dosing to a sampled effect variable, such as vasopressor or fluid dosing to blood pressure. Joosten et al. demonstrated the superiority of a closed-loop control system compared to manual administration of norepinephrine infusion to prevent hypotension defined as MAP < 90% of preoperative baseline [37]. The percentage of time patients had hypotension was 10 times less in the automated group than in the control group. Another challenge during intraoperative blood pressure management is the need for balanced fluid administration to maintain optimal cardiac output. Since this goal-directed therapy is based on assessing stroke volume variation, which may be error-prone, automation offers a significant advantage. In a multicenter prospective clinical trial, the patients in the automated software group received 89% of the recommended fluid boluses; of those, 66% resulted in a desired increase in the stroke volume compared to only 41% in the control group, $P < 0.001$ [41]. Furthermore, combining automated vasopressor and fluid management would allow personalized blood pressure management. Using a closed loop device to titrate both norepinephrine to maintain MAP within 10% of baseline and fluid boluses to maximize the stroke volume index has achieved a significantly better blood pressure control compared to manual titration [42••]. These early studies are promising, and larger studies are needed to investigate patient outcomes. In the future, combining the algorithms able to predict hypotension with the devices able to manage fluid and vasopressor administration presents another opportunity for innovation.

Depth of Anesthesia Control

In terms of computer-controlled administration of anesthesia, the effect site targets are not always well-delineated. The bispectral index (BIS) monitor is a form of processed electroencephalogram which produces a dimensionless number indicating the depth of anesthesia. This value has been an attractive target for research into computer-controlled infusion systems titrating sedative drugs though its proprietary nature has prevented better physiologic understanding of algorithmic dosing regimens. Lee et al. performed a study in which a deep learning model achieved a concordance correlation coefficient of 0.561 in predicting the BIS during a target-controlled infusion of propofol and remifentanil [43]. With the recent development of *Ibis*, an open-source algorithm functionally indistinguishable from the BIS monitor, researchers could now implement sophisticated control algorithms formerly requiring knowledge of the underlying process model (such as model predictive control) to titrate anesthetic medications [44]. With computer-controlled infusion systems already integrated into anesthetic care in 96 countries outside of the USA, their utility in automating intraoperative sedative dose adjustments is well-documented and a likely next step in the clinical practice of anesthesia [45].

Postoperative Surveillance

Postoperatively, remote monitoring of patients using automated software that ingests data from the EHR, vital sign monitors, and waveforms may lead to early detection of acute patient deterioration. In cardiac surgery patients monitored in ICU, using EHR and waveform data allowed accurate prediction of cardiovascular deterioration such as hypotension, escalated vasopressor needs, and low cardiac index [46•]. Similarly, a model was able to generate an accurate prediction of hypotension in the postoperative care unit using preoperative and intraoperative structured data [47]. Another system monitored 3926 hospital visits and analyzed 1,560,999 vital signs and 16,635 laboratory results, and generated 151 alerts, of which 143 (94.7%) were numerically accurate [48•]. Integrating such systems in clinical care would alert clinical providers to early changes in the patient's condition so that timely intervention can be initiated. These highly actionable alarms would occur at a rate that is unlikely to cause alarm fatigue [48•]. Such systems could decrease ICU admissions and rapid response calls [49••]; future work is needed to demonstrate the effect on patient outcomes.

Furthermore, machine learning may be utilized to predict, as far as 1 year after the surgery, the patient-reported outcomes such as patient well-being, chronic pain, and overall quality of life and thus can be applied before surgery to inform patients of the expected postoperative outcome [50]. Models were developed to predict the risk for an overnight stay after outpatient surgery [51], poorly controlled postoperative pain [52], need for opioid prescription after total knee arthroplasty [53], and unplanned 90-day hospital readmission [54]. Integrating models such as these into postoperative patient care may improve patient management by mobilizing multidisciplinary teams and highlighting opportunities for timely interventions, such as chronic pain service referral or multimodal pain control, which, in the long run, may lead to better patient satisfaction and outcomes.

Perioperative Efficiency, Case Length, and Discharge Planning

Recently, ML approaches have been used to predict the duration of operating room cases and assist in daily case management. A recent study demonstrated that better prediction of both case duration and time to discharge from the recovery room could be achieved using ML compared to statistical approaches. In this case, using data collected from 13,447 patients at an ambulatory surgery center, an ML model achieved a high predictive power, F1 score of 0.78–0.82, in determining the timely end of surgery by 5 pm and patient discharge by 7 pm if the cases were to start between 1 and 4 pm [55]. Using approaches like this one, better scheduling and staffing can be achieved, which ultimately can improve costs, efficiency, and patient satisfaction.

ML can also be used to aid in the risk assessment associated with discharging patients following general surgical procedures. A model trained on 15,201 surgical inpatients was able to classify patients by barriers to discharge, such as variations in clinical practice or nonclinical reasons, and predict the length of stay with a sensitivity of 56% and specificity of 83% [56]. Having an integrated system to identify discharge barriers and alert teams to patients who may be candidates for early discharge could allow for more focused discussions among multidisciplinary teams and efficient resource utilization. One benefit of this approach may be earlier discharge for patients in normal postoperative surgical pathways who may require shorter durations of postoperative monitoring.

Practical Considerations

Over the past 3 years, there have been significant advancements in AI technologies for anesthesiology. Data from the EHR, vital sign monitoring, imaging, waveforms, and wearables offer an exciting opportunity for clinically relevant insights, including predicting adverse outcomes, better monitoring, and improved resource management. The current research is focused on developing and optimizing AI models; much work remains to be done to demonstrate that AI technology can add value to clinical care, especially in improving patient outcomes. As most of the anesthesiology AI models are in the research phase, the next steps need to focus on external or prospective validation. Using limited data, especially retrospective data from a single center, may introduce bias in ML models, resulting in lower performance in other hospital systems. In addition, using data in which a bias based on patients' race, age, or gender will result in perpetuation of this bias [57]. Models based on large amounts of data from diverse populations should be extensively validated in order to mitigate bias [58]. In addition, the manuscripts reporting the development of the AI models should follow the standards for reporting AI research, including the validation, bias, and transferability of the findings [59, 60].

As these models become implemented in clinical practice, there are multiple ethical and regulatory considerations. The extent to which patients should be informed about the use of AI in their care is controversial. While most patients would accept AI technology if it were disclosed to them and supervised by their physician [61, 62], informing patients about AI may not always be possible or feasible. In addition, more guidance is needed in those cases in which the desired course of action based on the model and the anesthesiologist is different, as patient care is the responsibility of the practitioner. A possible solution will be the adoption of transparent AI approaches, which can provide an explanation of the model's predictions. For example, a model predicting a high risk for perioperative morbidity may display which risk factors were used and their relative significance in making the prediction. Based on analyzing the clinical factors that may have led to the model's determination, the anesthesiologist will be able to decide whether to accept or reject the model's predictions [47]. To achieve a better understanding, education on health AI needs to be a part of medical school [63] and residency curricula [64]. A thorough understanding of all details about how AI or ML models are developed is not necessary for physicians to use those models successfully; however, there should be rigorous testing, validation, and regulatory oversight. The first steps in regulating the use of health AI have been made in the USA [65] and Europe [66]. Therefore, removing the need for anesthesiologist oversight is in the distant future; in the near term, AI technology can augment the skills of the anesthesiologist in nearly every stage of perioperative care.

Conclusion

Artificial intelligence would allow anesthesiologists to harness large amounts of perioperative data. Multiple studies demonstrate the potential of AI-assisted technologies to provide clinically actionable insights and supplement the armamentarium of the anesthesiologist. From predicting the risk of complications to interpreting intraoperative data to make decisions on drug dosing and discharge planning, this technology has the potential to decrease physician workload while improving patient safety and outcomes. These early AI applications demonstrate promise in every area of perioperative care, and another opportunity for our specialty to embrace innovation is on the horizon.

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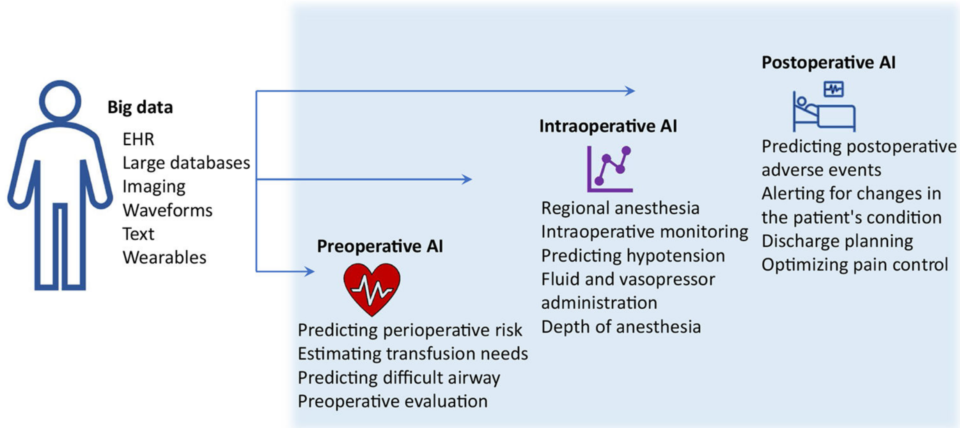

Fig. 1.

Artificial intelligence technologies in anesthesiology, developed using big data, can be applied to every stage of the perioperative care continuum. AI, artificial intelligence; EHR, electronic health record

Table 1

Number of FDA-approved artificial intelligence or machine learning enabled medical devices by specialty

Specialty	Number of approved medical devices that utilize AI technology
Radiology	392
Cardiovascular medicine	57
Hematology	15
Neurology	14
Clinical chemistry and microbiology	11
Ophthalmology	7
General, orthopedic, and plastic surgery	6
Gastroenterology and urology	6
Pathology	4
Anesthesiology	4
General hospital applications	3
Obstetrics and gynecology	1
Dentistry	1
Grand total	521

Table 2

Glossary of terms

Area under the receiver operator characteristic curve (AUC)	A measure of the predictive power of a model; takes values between 0 and 1; the closer to 1, the better the model is
Artificial intelligence (AI)	Computer systems that can perform tasks similar to human intelligence
Artificial neural network	A computer network similar to the ones in the human brain that can process information to gain insights from it
Big data	Data in large quantity, complexity, or at large speed, that is challenging to be processed using the traditional methods
Deep learning	A branch of AI focused on the development of artificial neural network models
Machine learning	Type of AI, that includes mathematical methods that allow continuous self-improvement through the use of data and experience, similar to the way the humans learn
Natural language processing (NLP)	Branch of AI that allows machines to process and understand human-generated text
Sensitivity	How likely a test is to detect a condition when it is truly present in a patient
Specificity	How likely is a negative test to rule out the presence of a disease in someone who does not have it
Xgboost	Commonly used and highly efficient machine learning algorithm