REVIEW ARTICLE

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# Artificial Intelligence in Surgery: Role of AI in Pre-Operative, Intra-Operative, and Post-Operative

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## ABSTRACT

Artificial intelligence (AI) can be used to improve surgical services at all stages, pre-operative, intra-operative, and post-operative. In the pre-operative stage, AI can be used to detect a disease, classify diseases, segment the results of radiological examinations, facilitate the process of registering patient data, provide advice in decision-making, and provide prognosis predictions for the results of surgical procedures to be performed. At the intra-operative stage, AI can be used to generate 3D reconstructions during the surgical process, improve navigation capabilities during endoscopic procedures, provide tissue tracking features, enable the use of augmented reality during surgery, and improve the efficiency of surgical robots in minimally invasive surgeries. In the postoperative stage, the use of AI can mainly be used in the automated processing of electronic health records data.
**Key words:** artificial intelligence, surgery, computer vision

**Abbreviations:**
AI: Artificial Intelligence;
ML: Machine learning;
RL: Reinforcement Learning;
CV: Computer Vision;
CNNs: Convolutional neural networks;
NLP: Natural Language Processing;
DCNN: Deep Convolutional Neural Network;
DRL: Deep Reinforcement Learning;
RNNs: Recurrent neural networks;
CRP: C-reactive protein;
AAA: Abdominal Aortic Aneurysm;
PCA: Principal Component Analysis;
SSM: Statistical Shape Model;
PLSR: Partial Least Square Regression;
SLAM: Simultaneous Localisation and Mapping;
AR: Augmented Reality;
MIS: Minimally Invasive Surgeries;
RAS: Robotic and Autonomous Systems;
EHR: Electronic Health Records;
GB: gigabytes;
EHRs: Electronic Health Records;
AUC: area under the curve;
AR: augmented reality.

## INTRODUCTION

The concept of Artificial Intelligence (AI) originated from the research conducted by Alan Turing, although John McCarthy was the first to coin this term during the Dartmouth Summer Research Project in 1956 (1). Artificial Intelligence is the outcome of merging numerical computations with computer assistance to generate intelligence. Authors often argue that AI generates computer-generated simulations with three main objectives: analysis, comprehension, and prediction (2). Another definition characterises AI as machines that operate in a proactive and suitable manner (3). Taking these definitions into account, it is fair to say that AI refers to the utilisation of a computer to analyse data, make decisions, or aid in completing tasks.

The word AI has grown difficult as it supplants technical expressions such as machine learning. AI is an expansive classification that encompasses subfields such as machine learning, which involves methods like neural networks and deep learning. *Fig. 1* depicts an AI taxonomy that elucidates the connections between various subjects. The various subfields mentioned are interconnected,

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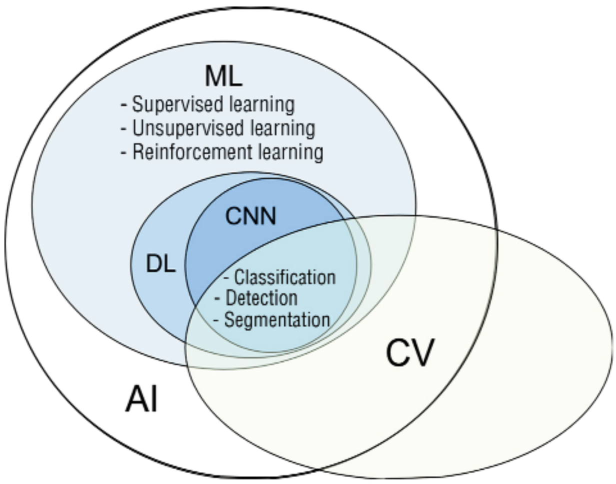


**Figure 1 - Basic terminology in AI. AI – artificial intelligence; ML - machine learning; DL - deep learning; CN - convulational neural network; CV - commputer vision**

and depending on the specific use case, techniques from one subfield can be merged with or incorporated into another (4).

## *Classification of AI*

### *Machine learning*

Machine learning (ML) is the field of research that focuses on developing and utilising statistical models and techniques to enable machines to acquire knowledge and perform tasks. Machine learning methods utilise inherent qualities or attributes within the data to perform tasks, without the need for explicit programming. Typically, these tasks are divided into two distinct categories: those that involve regression (i.e., creating a model to understand the relationship between continuous variables) and those that include classification (i.e., dividing data into different groups). In conventional machine learning, human attributes are manually selected or generated to guide the algorithms in evaluating specific aspects of the data during analysis. On the other hand, neural networks automatically extract traits, which will be explored later (4).

Supervised and unsupervised learning are the primary modalities of machine learning. Supervised learning is training an algorithm to make predictions based on a specified output. This process necessitates the use of labelled data sets that are divided into training and test sets for evaluation (5). On the other hand, unsupervised learning includes identifying patterns in data that does not have any predetermined annotations. It has the capability to discern connections between groups, such as clustering, and produce hypotheses for subsequent research. This can be applied to more specific data sets, such as surgical motion and activity, as well as to more general surgical data, such as patient outcomes databases. Unsupervised learning has been utilised, for example, to automatically detect suturing movements in surgical recordings and to identify patients undergoing heart surgery with a high risk of complications (6,7).

Reinforcement Learning (RL) is an unsupervised learning method that belongs to the third category of learning. It can be likened to operant conditioning, where the model learns by repeatedly attempting different actions, with rewards and punishments influencing the model's behaviour to maximise rewards (5,8).

### *Artificial neural networks*

In traditional machine learning, features, also known as variables, are manually chosen by an individual to optimise performance for a certain task. Whiskers and pointy ears might be regarded as meticulously designed characteristics in a task of recognising a cat. Neural networks, drawing inspiration from organic nervous systems, employ layers of fundamental computer units designed to mimic neurones for the purpose of analysing input (*fig. 2*). Unlike standard machine learning, neural networks have the ability to extract features from data and utilise them as inputs. Subsequently, the system can adjust the weights of the features to be utilised within an activation function, thereby generating an output (9). In essence, the system autonomously alters the weights to enhance or diminish connections within the network, aiming to achieve optimal results through predetermined mathematical algorithms.

### *Deep learning*

Deep neural networks are neural networks with three or more layers, allowing them to learn complex

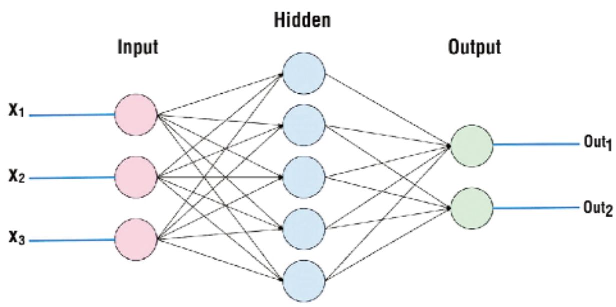


**Figure 2 - Three-layer of neural network**

patterns that cannot be observed in simple one- or two-layer networks. Like traditional neural networks, deep learning selects features based on their probability of yielding the highest results. This approach is highly efficient for handling unorganised data, such as images, videos, and audio. In a deep neural network, each layer performs a set of operations to generate a representation of the input, which is then passed on to the next layer (10). Increased depth in network layers results in the creation of more abstract data representations, even while it enhances the distinction of data classes (11). Currently, convolutional neural networks, recurrent neural networks, and residual neural networks are commonly employed deep learning architectures in surgical applications.

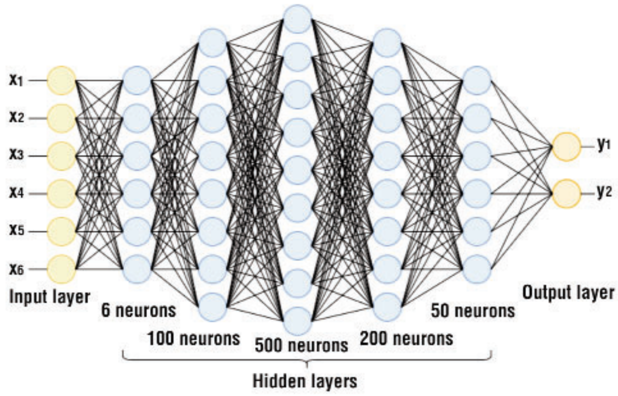


**Figure 3 - Ilustration of deep learning**

## *Applications of Artificial Intelligence*

The previously stated methods have demonstrated significant potential in diverse domains of artificial intelligence. Natural language processing and computer vision have gained significant popularity in the field of medicine, especially in surgery.

### *Computer vision*

Computer Vision (CV) is a branch of artificial intelligence that focuses on the analysis and understanding of images and videos using machine learning techniques (5). It involves various processes such as image processing, pattern recognition, and signal processing (*fig. 3*; it is important to highlight that although CV does not encompass reinforcement learning, this is just a situation where the two fields overlap). It involves a system that integrates data from the individual pixels of an image, detects objects in the image, and potentially examines the empty spaces inside the image. By combining these components, it is possible to construct advanced applications, such as autonomous driving systems that utilise computers to identify items such as traffic signals, pedestrians, and open roadways. Convolutional neural networks (CNNs) have also demonstrated significant advantages for CV tasks (4).

With the increasing availability of visual surgical data, the field of CV is finding more and more applications in surgery. With the increasing user-friendliness of laparoscopic, endoscopic, and robotic camera systems, as well as the decreasing cost and bigger storage capacity, an increasing number of surgeons are choosing to document their procedures for the sake of research, teaching, and education (4).

### *Natural language processing*

Natural Language Processing (NLP) involves not only the identification of vocabulary, but also the development of machines that can understand human language. This entails comprehending synonyms, antonyms, definitions, and other interconnected facets of language. In the absence of NLP, computers are limited to interpreting machine languages or code (such as C, Java, and Visual Basic) and executing instructions that have been explicitly written and compiled into an output. NLP enables machines to have a basic understanding of human language as it is commonly utilised in everyday situations. The goal is to understand the structure and meaning of phrases, sentences, or paragraphs by focusing on syntax and semantics (12).

NLP is employed for the analysis of electronic medical records and the completion of dictation duties performed by healthcare personnel. The capability of NLP to analyse specific types of human language allows for the automatic evaluation and organisation of unstructured free text, such as radiology reports, progress reports, and operation notes. For example, sentiment analysis in patient notes can be utilised to anticipate a patient's health condition, while record analysis can be employed to forecast the probability of cancer in a patient (4).

## *Artificial Intelligence in preoperative*

### *Detection*

Regions of interest are identified and located in space through the process of detection, which may also include classifying the regions or the entire image. Regions of interest are commonly depicted using bounding boxes or landmarks. Similarly, techniques utilising deep learning have shown promise in detecting various anomalies or medical conditions. Regression layers are employed to determine the parameters of the bounding box, whereas convolutional layers are commonly utilised in Deep Convolutional Neural Network (DCNN) for the purpose of detection (13).

A deep convolutional autoencoder was trained on 4D positron-emission tomography pictures to extract both statistical and biological information. The training aimed to detect prostate cancer by analysing the data extracted from the images (14). In the case of diagnosing pulmonary nodules, it was recommended to use a 3D CNN with roto-translation group convolutions (15). The device has excellent sensitivity, accuracy, and convergence speed.

The utilisation of dynamic contrast-enhanced MRI was employed to formulate a search policy with the objective of finding breast lesions. The deep Q-network was expanded, and subsequently, Deep Reinforcement Learning (DRL) was utilised to acquire knowledge of the search policy (16). Lee et al. utilised an attention map and an iterative process to imitate the workflow of radiologists, aiming to detect acute cerebral bleeding from CT scans and improve the interpretability of the network (17).

### *Classification*

The input, comprising one or more medical pictures or volumes of organs/lesions, undergoes classification to ascertain its diagnostic significance. Deep learning-based approaches are becoming increasingly popular, alongside standard machine learning and image analysis techniques (18). These systems utilise convolutional layers to extract input information and fully connected layers to determine the diagnostic value.

An example of a classification pipeline was presented to segment bladder, breast, and lung tumours using Google's Inception and ResNet architecture (19,20). Chilam Kurthy et al. showed that deep learning can identify cerebral haemorrhage, midline displacement, calvarial fracture, and mass effect from head CT scans. Recurrent neural networks (RNNs) are more precise in predicting postoperative haemorrhage, death, and renal failure in patients receiving cardiosurgical care compared to standard clinical methods. This prediction is done in real time (21). ResNet-50 and Darknet-19, which have similar sensitivity but improved specificity, are used to detect whether tumours in ultrasound images are benign or malignant (22).

### *Segmentation*

Segmentation categorizes pixels or voxels in an image. Previously, computation required dividing images into smaller panes. CNNs predicted the target label at each window's center. Many windows were fed into the Convolutional Neural Network to partition an image or voxel. DeepMedic identified and separated brain tumors from MRI scans well (23). Due to ongoing network function computation in areas with several overlapping windows, sliding window-based methods are wasteful. Fully Convolutional Networks succeeded it. By replacing fully connected layers with convolutional and upsampling layers in a classification network, FCNs improve segmentation efficiency (24). U-Net and other encoder-decoder networks have shown promising medical image segmentation outcomes (25,26). These encoders use many convolutional and downsampling layers to extract visual data at different sizes. The decoder's convolutional and upsampling layers recover feature map spatial resolution to segment pixels and voxels accurately. Zhou and Yang analyze numerous normalization methods used to train U-Net models for medical picture segmentation (27).

### *Registration*

Registration refers to the process of spatially aligning two medical volumes, modalities, or images. It is particularly essential for organising both the pre- and intraoperative operations. Historically, medical image registration algorithms have typically relied on iterative optimisation of a parametric transformation in order to minimise a given measure. Deep regression models are supplanting optimization-based registration processes, such as mean square error or normalised cross-correlation, in order to provide quicker and more effective processing of medical input (13).

### *Decision aids*

Decision aids include background data, diagnosis and treatment alternatives, pros and cons, and prediction of outcomes for specific patient populations. A systematic analysis of 31,043 patients who had to make screening or treatment decisions indicated that decision aids improved informed and active participation (28). A comprehensive study of 17 surgical patient trials found that decision aids boosted treatment awareness and desire for less invasive procedures. Death, morbidity, quality of life, and anxiety were not significantly different (29). Decision aids are created for different patient groups with a single clinical presentation or option, hence they do not account for individual patients' physiology and risk factors.

### *Prognostic scoring systems*

Prognostic scoring systems utilise regression modelling to analyse data from patient groups in order to identify risk factors for individual patients. An elevation in the concentration of C-reactive protein (CRP) in the bloodstream following colorectal surgery is associated with the occurrence of anastomotic leak. Based on a meta-analysis, the optimal cutoff value for C-reactive protein (CRP) on the third day following surgery is determined to be 172 mg/L (30). Nevertheless, this technique lacks complete accuracy as it fails to reflect the underlying pathology. C-reactive protein (CRP) levels vary along a range and are directly linked to the presence of inflammation, with a reasonably stable period of time it takes for the levels to decrease by half. Following a colectomy, medical experts utilise CRP levels as a means of identifying any potential issues. However, the diagnosis of a problem does not rely on the CRP levels being above or below the 172 mg/L criterion (31). A CRP level below the cutoff often indicates the absence of problems, with a negative predictive value of 97%. Nevertheless, the positive predictive value is at a mere 21%, suggesting that a high CRP level does not definitively indicate a post-operative problem (32-34).

Prognostication scoring systems may involve a wide range of criteria. These systems are used to forecast stroke and serious gastrointestinal bleeding, as well as to assess the severity of an illness. The reason for this is that most diseases are not attributed to a single physiological factor (32-34). Regression analysis, which is used in prognostic scoring systems, assumes linear relationships between input variables (35,36). However, in cases of non-linear relationships, the scoring system becomes as unpredictable as flipping a coin (37).

Prognostic scoring systems have been integrated as digital tools to calculate risk and assist with clinical application. An example of a widely recognised tool is the NQIPSurgical Risk Calculator. The utilisation of calculators may increase the likelihood of patients adopting risk-reduction strategies such as prehabilitation. However, further development is necessary as the input variables need to be manually provided and the predicted accuracy is suboptimal, especially for non-elective procedures.

## ***Artificial Intelligence in intraoperative***

### *Instantiating 3D shapes*

3D reconstruction can be performed using MRI, CT, or ultrasound imaging during surgery. An application can be utilised to generate a three-dimensional surgical environment in real-time, hence diminishing the quantity of photographs required for three-dimensional reconstruction. In addition, improved techniques can boost the clarity of the reconstruction even further. A developing area of research involves generating a real-time representation of a 3D shape during surgery using only one or a few 2D images (13).

For instance, a 3D prostate shape was constructed by utilising a radial basis function and multiple non-parallel 2D ultrasound images (38). Similarly, the 3D shapes of stent grafts in different states (fully deployed, fully compressed, and partially deployed) were generated through mathematical modelling, a reliable perspective-n-point approach, graft gap interpolation, and graph neural networks (39-41). These shapes were created from a single 2D fluoroscopy projection using a technique called instantiation (42). To improve the efficiency of the framework used to create the shapes and automatically segment markers on stent grafts, a focused U-Net with equal weighting was proposed. A 3D model of an Abdominal Aortic Aneurysm (AAA) was created using skeleton deformation and graph matching techniques with only one 2D fluoroscopy projection (43). Three mathematical techniques, Principal Component Analysis (PCA), Statistical Shape Model (SSM), and Partial Least Square Regression (PLSR), were used to create a 3D shape of a liver from a single 2D projection (44). A framework for shape instantiation without registration was developed and expanded to include sparse PCA, SSM, and kernel PLSR (45). A new technique using deep and one-stage learning has been developed to create 3D shapes. This method enables the creation of a three-dimensional point cloud using only one two-dimensional image (46).

### *Endoscopic navigation*

The prevailing direction in surgery is increasingly shifting towards endoscopic and intraluminal procedures that depend on prompt identification and intervention. An evaluation has been conducted on the capacity of navigation systems to guide the movement of endoscopes towards particular locations. Depth estimation, visual odometry, and Simultaneous Localisation and Mapping (SLAM) techniques have been specifically designed to enable camera localisation and environment mapping using endoscopic images (13).

Accurate depth estimation from endoscopic pictures is essential for mapping the 3D structural environment and estimating the 6 degrees of freedom camera movements. This has been achieved through the use of self-supervised or supervised deep learning techniques (47-50).

Visual odometry is a process that determines the position and orientation of a camera that is in motion by analysing a sequence of video frames. CNN-based algorithms were employed for camera pose estimation, utilising temporal information. The evaluation of visual odometry-based localisation techniques was limited to lung phantom and GI tract data (51,52).

Navigation requires real-time 3D reconstruction and localization of surrounding tissue due to tissue dynamics. Simultaneous Localisation and Mapping (SLAM) is a well-studied robotics approach. Using Simultaneous Localization and Mapping (SLAM), the robot can properly locate the camera on its map. Additionally, it can create a three-dimensional image of its surroundings. Traditional SLAM approaches assume a rigid environment, which is not true in a surgical setting where soft tissues and organs may flex. Thus, the misconception limits the use of this technology in surgery. Mountney et al. examined how breathing-induced soft tissue movement affects SLAM estimate using a stereoendoscope and EKF-SLAM (53). Monocular EKF-SLAM was used to assess hernia anomalies during hernia repair surgery by Grasa et al (54). Turan et al. calculated RGB depth images using form from shading. Later, they developed RGB D SLAM employing RGB and depth images (55). Song et al. developed a CPU-based ORB SLAM and a GPU-based dense deformable SLAM to improve stereoendoscope localization and mapping (56).

### *Tissue feature tracking*

Minimal Invasive Surgery uses learning methods for soft tissue monitoring. Mountney and Yang created an online learning system that uses decision tree categorization to pinpoint relevant traits (57). The feature tracker is updated over time using this method. Ye et al. identified and focused on GI soft tissue surfaces. They used an online random forest and a structured SVM for this (58). Wang et al. used a statistical appearance model in their region-based 3D tracking system to differentiate organs from background (59). The validation findings revealed that learning algorithms can improve tissue tracking robustness to deformations and illumination changes.

### *Augmented reality*

Augmented Reality (AR) overlays a partially transparent preoperative image onto the focal area to improve surgeon vision (60). Wang et al. used a projector to display the AR overlay during oral and maxillofacial surgery, according to their article (61). To align the virtual image and teeth, 3D contour matching was used. Instead of projectors, Pratt et al. used Hololens to display a 3D vascular model on patients' lower limbs (62). For AR navigation, Zhang et al. devised a framework that automatically registers 3D deformable tissue. They did this using Iterative Closest Point and Random Sample Consensus (63). Projecting the overlay over markerless deformable organs is tough, therefore this was crucial.

### *Robotics*

Artificial intelligence has enhanced the efficiency of surgical robots in Minimally Invasive Surgeries (MIS). The objective is to enhance their perception, decision-making, and focused activities (63,64). The primary areas of emphasis for AI techniques in Robotic and Autonomous Systems (RAS) include perception, localisation and mapping, system modelling and control, and human-robot interaction.

## ***Artificial Intelligence in the postoperative period***

### *Automated electronic health records data*

The Health Information Technology for Economic and Clinical Health Act of 2009 promoted the adoption of Electronic Health Records (EHR) systems (65). Within a span of less than 6 years, over 80% of US hospitals successfully implemented EHRs (66). These systems generate a substantial volume of data, which is expected to continue increasing in the future. In 2013, around 153 billion gigabytes (GB) of data were generated, and it is projected to expand annually by 48% (67). This large amount of data is ideal for artificial intelligence models that are designed to handle big datasets.

Artificial intelligence models possess the capability to generate real-time forecasts and suggestions due to the automatic updating of Electronic Health Records (EHRs) when fresh patient data is accessible. Recent publications demonstrate the viability of this approach. The MySurgeryRisk platform utilises EHR data on 285 variables to forecast 8 potential complications after surgery. The platform achieves an area under the curve (AUC) ranging from 0.82 to 0.94 for these complications. Additionally, it predicts the likelihood of mortality after 24, 36, and 1 year with an AUC ranging from 0.77 to 0.83. The programme receives data from electronic health records automatically, eliminating the requirement for human data entry and search. This removes a significant obstacle to clinical application. In a prospective study, the system demonstrated superior accuracy in identifying postoperative difficulties compared to doctors (68).

## CONCLUSION

AI is the outcome of merging numerical operations with computer aid to generate intelligence. AI can be considered as a broader umbrella term that encompasses subfields such as machine learning, which in turn includes techniques like neural networks and deep learning. Natural language processing and computer vision are widely utilised in the field of medicine, with a particular emphasis on their application in surgical procedures. AI can assist in preoperative, intra-operative, and postoperative stages of surgery. AI can assist in preoperative procedures by aiding in the diagnosis and facilitating surgical decision-making. During surgery, AI may assist us in several ways, including creating three-dimensional (3D) models of shapes, guiding endoscopic navigation, tracking tissue features, implementing augmented reality (AR), and controlling robotic systems. Artificial intelligence can be utilised to automate electronic health records in the postoperative setting. Although AI developments have made it possible to provide surgical assistance, there are some challenges that must be solved from a practical perspective. It is necessary to redevelop data availability, data annotation, data standardisation, technical infrastructure, interpretability, safety, monitoring, ethics, and legal considerations. As a result, surgeons must be prepared to not only embrace this transformation but also actively participate in its development and implementation.

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