Medical Robotics

REVIEW ARTICLE

The clinical application of artificial intelligence technology in spinal surgery

Zihe Feng[#], Honghao Yang[#], Xinuo Zhang[*], Yong Hai[*]

Department of Orthopedic Surgery, Beijing Chao-Yang Hospital, Beijing 100020, China

ABSTRACT

Artificial intelligence (AI) is a field that investigates how to endow computers and computer-controlled machines with the capability to imitate human intelligence. As a significant driving force for the new wave of technological revolution and industrial transformation, AI has emerged as a research hotspot in the medical domain. The progress in AI technology has profoundly influenced medicine, particularly offering new opportunities for precision and automation in spinal surgery. AI, a comprehensive field, encompasses a variety of research areas such as machine learning (ML), deep learning (DL), computer vision, natural language processing, and robotics, among others. These subfields intersect and potentially overlap to a significant degree. Furthermore, robotics and AI, closely intertwined, maintain a symbiotic relationship. AI, a discipline within computer science, aspires to develop and implement intelligent machines, with robots exemplifying these creations in physical form. AI equips robots with capabilities for environmental comprehension, information processing, decision-making, and learning. This review aims to examine the clinical application of AI technology in spinal surgery, with a focus on traditional ML, DL, and robotics. We will discuss the merits and drawbacks of these technologies, as well as future development trends.

Key words: Artificial intelligence, spinal surgery, robot, machine learning, deep learning

INTRODUCTION

Artificial intelligence (AI), progressing rapidly in recent years, seeks to replicate and amplify human cognition using computational technologies. The prevalent application of AI methodologies in diverse disciplines, a notable contemporary trend, stems from multidisciplinary amalgamation. A salient instance of this amalgamation is the confluence of AI with medicine.[1] Serving as a pivotal catalyst for the current technological revolution and industrial metamorphosis, AI has burgeoned into a focal area of research within the medical field. Advances in AI have substantially reshaped the landscape of medicine, specifically bestowing unprecedented opportunities for precision and automation within the realm of spinal surgery.[2]

AI technology encompasses machine learning (ML), deep learning (DL), and other techniques, which are extensively employed in spinal surgery.[3] These technologies facilitate swift and accurate diagnosis of spinal diseases, assist doctors with preoperative planning and postoperative outcome prediction, and help improve diagnostic efficiency, alleviate medical staff workload, and reduce misdiagnosis rates. Consequently, they promote intelligent diagnosis, treatment, and prognosis of spinal diseases.

[#]These authors contributed equally to this work.

***Corresponding Author:**

Xinuo Zhang, Department of Orthopedic Surgery, Beijing Chao-Yang Hospital, Gongti South Road No. 8, Beijing 100020, China. E-mail: coolmanchine@163.com; https://orcid.org/0000-0002-7817-4241

Yong Hai, Department of Orthopedic Surgery, Beijing Chao-Yang Hospital, Gongti South Road No. 8, Beijing, China. E-mail: yong.hai@ccmu.edu.cn; https://orcid.org/0000-0002-7206-325X

Received: 25 July 2023; Revised: 7 August 2023; Accepted: 1 November 2023; Published: 21 November 2023

https://doi.org/10.54844/mr.2023.0428

For spine surgeons, surgery is a key part of clinical work, while the traditional surgical method is that the doctor uses hand tools to perform open surgery. With the rapid development of AI and mechanical control technology, spinal surgery technology is developing towards data-driven intelligent human-machine collaboration. Medical robotics, a novel interdisciplinary research field, involves AI technology and integrates various AI techniques such as mathematical analysis, computer vision, and computer graphics.[4] Spinal surgery, a highly complex and technically demanding procedure for treating spinal diseases, has undergone significant changes with the development of surgical robot technology, resulting in a more precise, safe, and efficient surgical process.[5]

This review aims to examine the clinical application of AI technology in spinal surgery, with a focus on traditional ML, DL, and robotics. We will discuss the merits and drawbacks of these technologies, as well as future development trends.

TRADITIONAL MACHINE LEARNING

Methodology

ML, a crucial branch of AI, involves the use of diverse algorithms to derive data features, establish rules, formulate models, and analyze novel data, ultimately improving model performance through knowledge acquisition. ML is classified into supervised, and unsupervised learning, each necessitating distinct data support. It is important to note that the hierarchical relationship between DL and ML is a topic of scholarly debate. For the purposes of this article, traditional ML and DL are treated as parallel entities.

Supervised learning

Supervised learning relies on labeled training data to map inputs to outputs, where each sample is linked to a specific target output. The model aims to learn this correlation to predict future data. It primarily handles regression for continuous variables using algorithms like linear and logistic regression, and classification for discrete variables with tools such as support vector machines, decision trees, and random forests.

Traditional ML methods have found numerous applications in the preoperative planning, diagnosis, postoperative care, and outcome prediction in spinal surgery. For instance, Wang *et al*. carried out a retrospective study utilizing data from 184 consecutive patients with cervical spondylotic myelopathy after posterior laminectomy and fusion. Clinical and imaging variables were gathered for univariable and multivariable logistic regression analyses. Based on previous literature and clinical expertise, a selection of variables was employed to construct a support vector machine (SVM) ML model for C5 palsy prediction.[6]

Unsupervised learning

Unsupervised learning, on the other hand, uncovers underlying structures and patterns in unlabeled datasets without predefined target outputs. It independently discerns features and relationships in data, aiding subsequent analysis and decision-making. Its key tasks encompass clustering and dimensionality reduction.

Unsupervised learning is less exploited in spinal disorders research compared to supervised ML. DeVries *et al.* evaluated the performance of an unsupervised k-means ML algorithm against a logistic regression model in predicting walking ability among spinal cord injury patients with comprehensive admission neurological information.[7]

In the last three years, more and more researchers use one or more above algorithms in their studies to build clinical models and validate model performance in a similar manner. Wang *et al.* 's study sought to construct and validate supervised ML models to predict surgical site infection (SSI) risk following minimally invasive transforaminal lumbar interbody fusion (MIS-TLIF). Relevant factors were integrated into six ML algorithms: k-nearest neighbor (kNN), decision tree (DT), SVM, random forest (RF), multi-layer perceptron (MLP), and Naive Bayes (NB). These algorithms were applied to develop a prediction model for SSI risk post MIS-TLIF under quadrant channel.[8]

In the study conducted by Dong *et al.*, predictive elements of blood transfusion were identified from all spinal tuberculosis cases treated through spinal fusion. The identification process employed a nomogram and an array of ML algorithms, including SVM, DT, MLP, NB, k-NN, and RF.[9] The models' performance of above study was both evaluated through metrics such as the area under the receiver operating characteristic (AUC), sensitivity, specificity, and accuracy (ACC). And a 10-fold cross-validation was employed during the training process.

Application

ML methodologies have displayed remarkable potential in numerous areas, including spinal surgery. Incorporating ML approaches in disease diagnosis, and postoperative care has resulted in substantial improvements in spinal surgery outcomes.

Machine learning for preoperative planning and diagnosis

ML algorithms have demonstrated potential in the preoperative planning phase, facilitating precise diagnoses and the selection of suitable surgical candidates. For example, ML models have been employed to identify patients eligible for single-level outpatient anterior cervical discectomy and fusion (ACDF), thereby supporting surgeons in making informed decisions.[10] Furthermore, ML approaches have been applied to forecast various clinically relevant outcomes in lumbar spinal stenosis decompression surgery, potentially enabling improved patient consent and personalized shared decision-making.[11]

Machine learning for postoperative care and outcomes

ML models are increasingly applied to anticipate postoperative complications and oversee patient recovery. For instance, ML techniques have been utilized to create and externally validate predictive models for spinal surgery outcomes, identifying crucial predictors such as age, baseline scores, degenerative pathology type, prior spinal surgeries, smoking status, morbidity, and hospital stay duration.[12] This allows for personalized management strategies. Moreover, ML algorithms have been employed to estimate the risk of surgical site infections following spinal fusion procedures, facilitating proactive infection prevention measures and enhancing clinical decision-making and perioperative management optimization.[13,14]

DEEP LEARNING

Methodology

DL is a ML subfield that seeks to emulate the human brain's mechanisms using data, enabling computer systems to automatically obtain multi-layered abstract representations and learn collective behaviors. Unlike traditional ML (shallow learning), DL distinguishes itself in data representation, feature engineering, learning samples, algorithms, and opacity. Consequently, this review treats DL as a separate topic alongside traditional ML. DL algorithms, exemplified by various artificial neural networks (ANN), excel at analyzing and efficiently processing massive medical data. Distinct from the previous individualized orthopedic medical models, big data-based prediction models offer optimal treatment plans that are efficient, effective, and minimize adverse events. Furthermore, owing to its ability to abstract multi-level features through multiple hidden layers in neural networks, DL has become the most widely used model in the medical imaging field. Its robust generalization capacity and nonlinear mapping ability further contribute to its widespread adoption.

Artificial neural network

The different types of neural networks utilized in DL include convolutional neural networks (CNNs), U-Nets, and MLPs, each with distinct functions. CNNs, designed to automatically and adaptively learn spatial hierarchies of features, are typically used for image recognition.[15] U-Nets, on the other hand, are particularly suited to biomedical image segmentation due to their symmetrical architecture, allowing precise localization.[16] Lastly, MLPs, with their ability to learn a nonlinear function mapper, are used for approximation, classification, and prediction tasks, often serving in diagnosis and prognosis of diseases.[17]

The application of ANN necessitates a methodical approach, which encompasses data acquisition and preprocessing, model development and validation, and clinical implementation. Of these stages, model training, validation, and testing are particularly pivotal. Following data preprocessing, ANNs, the architecture of which may differ (*e.g.*, CNN, pooling, and fully-connected layers), are trained using this data. This process enables the model to discern pertinent features from the data, thereby facilitating accurate predictions. Subsequent to training, the model undergoes validation with a distinct dataset, not utilized during the training phase, to estimate its performance on novel, unobserved data. Upon successful training and validation, the ANN can transition into clinical practice, where its predictive capabilities can inform preoperative planning, intraoperative navigation, postoperative evaluation, and even resident education. Post-deployment monitoring of the model's performance is essential to facilitate ongoing refinements, informed by feedback from the clinical setting.

It is important to acknowledge that the specified methodology may require considerable adaptation, contingent on the particular application, data availability, and distinct surgical procedure requirements.

Application

Deep learning in spinal image recognition

Image recognition is the process of identifying and detecting objects or features in digital images. The different kinds of CNN is a popular DL algorithm used for this purpose. Konya *et al.* employed diverse segmentation models for the identification of vertebral bodies in lumbar lateral X-ray images. These models encapsulate semantic segmentation models (such as U-Net, Pyramid Scene Parseing Network, and DeepLabv3) and instance segmentation models (including Mask R-CNN and YOLACT).[18]

Deep learning in spinal image segmentation and measurement

Image segmentation is a critical step in medical image analysis that involves partitioning an image into multiple segments. Das *et al.* introduced a novel deep neural network architecture coined as "RIMNet", a region-to-image matching network model, and these models can automatically identify and segment intervertebral discs from multimodal magnetic resonance imaging (MRI) images.[19] Several researchers have proposed an automated DL framework based on an ensemble of U-Nets to perform vertebral morphometry and measure the Cobb angle directly on three-dimensional (3D) computed tomography (CT) images of the spine.[20]

Deep learning in spinal disease diagnosis

DL algorithms have been employed to diagnose a variety of spinal diseases, such as tumor,[21] infection,[21] osteoporosis,[22] scoliosis,[22] fracture[23] and degenerative disease.[24] For instance, CNNs demonstrated high accuracy in differentiating between normal and stenotic lumbar spine on MRIs.[25]

In conclusion, DL, with its diverse neural networks, is revolutionizing spinal imaging, aiding in image recognition, segmentation, measurement, and disease diagnosis.[26–28] However, further research is needed to refine these algorithms and validate their clinical utility.

SPINAL ROBOTIC SYSTEM

Methodology

The maturation of surgical robots has been facilitated by advancements in multidisciplinary fields such as electronics, computer science, and AI.[4] Like conventional surgery, surgical robots adhere to the perception-decision-execution loop. Assisted by AI, these robots can integrate preoperative, intraoperative, and operation-related patient data. Interpretable AI algorithms, which leverage clinical big data and multimodal imaging data, can offer more precise surgical planning, acting as a valuable supplement for surgeons.

Robotic-assisted spinal surgeries, prevalent worldwide, predominantly employ a suite of instruments including preoperative CT scanners, C-arm fluoroscopes, physician workstations, and spine-specific surgical robots (Figure 1). There are two main technical strategies in these procedures: One leveraging preoperative planning based on preoperative CT and intraoperative two-dimensional imaging, and the other predicated on intraoperative planning using real-time three-dimensional images.

The first strategy deploys a series of tools—two-dimensional C-arm fluoroscope, physician workstation, navigation system, and spinal surgical robot—for a distinct workflow. Initially, a preoperative CT scan obtains a three-dimensional image of the surgical site, which subsequently undergoes segmentation and reconstruction to create a virtual 3D vertebra. This image aids the surgeon in preoperative planning. During the operation, the C-arm fluoroscope captures two-dimensional images of the patient's vertebra, which are then correlated with the preoperative CT scan using graphic registration algorithms. This process necessitates two separate two-dimensional X-ray images taken from varied angles for precise alignment with the preoperative plan. The subsequent surgical operations, executed manually or robotically, are guided by real-time navigation and automatic positioning of the robotic arm.

Conversely, the second strategy circumvents the need for preoperative CT scans. It involves intraoperative scanning of the surgical site using a three-dimensional C-arm or O-arm, followed by coordinated alignment of the robot arm, surgical site, and navigation equipment in space. Post-alignment, intraoperative planning occurs, guiding the subsequent surgical operations. These operations, carried out as per the established positioning and direction, are supplemented with navigation system-verified implant placement, culminating in the conclusion of the surgical procedure.

The strategy above not only encompass the field of AI but also integrate mathematical analysis, material science, and biomechanics. Many initial reports demonstrate that, through multidisciplinary collaboration, robotic assistance greatly enhances the visual and tactile aspects of spinal surgery, leading to safer, more accurate outcomes and facilitating repeatable procedures.[29–31]

Application of spinal robot

Since the first-ever widely utilized SpineAssist robot (Mazor Robotics Ltd., Caesarea, Israel) received the Food and Drug Administration (FDA) approval in 2004,[32] an increasing number of surgical robots are being employed in operating rooms, serving as valuable assistants to spinal surgeons. By offering real-time intraoperative navigation and rigid stereotaxy, this technology holds the potential to enhance precision while reducing radiation exposure, complications, operation duration, and recuperation time.[33,34] Presently, robotic assistance is mainly used in spinal fusion and instrumentation procedures and enables the completion of complex and high-risk operations, including spinal tumor resections and deformity corrections, that were previously challenging to perform.[35,36]

This review mainly introduces two commonly used robots, American widely used one, MAZOR X STEALTH EDITIONTM (Medtronic, USA) and Chinese widely used one, TiRobot II (Beijing Tinavi Medical Technologies Co., Ltd., China).

Mazor X® and MAZOR X STEALTH EDITION™

Mazor X®, the predecessor to MAZOR X STEALTH EDITION™, was introduced by Mazor Robotics Ltd. during the 2016 North American Spine Society (NASS) annual meeting. The Mazor X platform offers two registration and planning modes for enhanced surgical

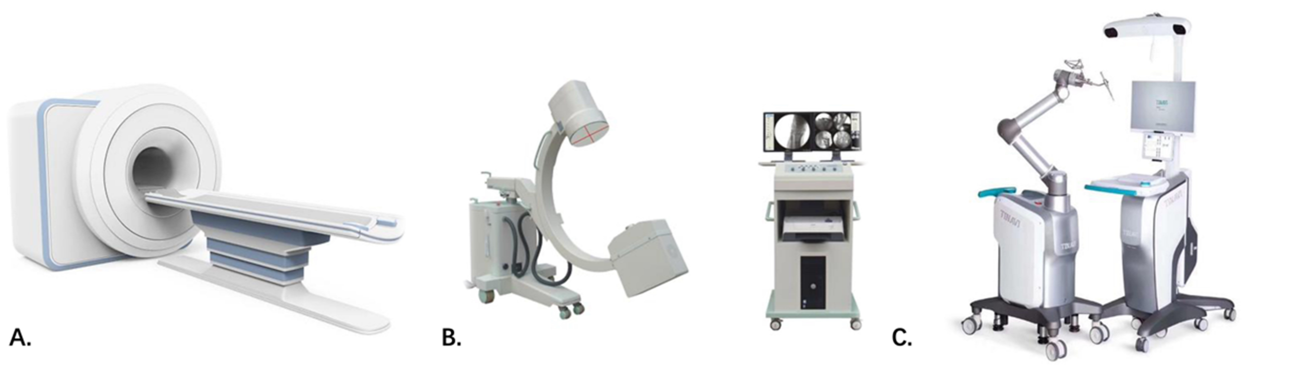

Figure 1. The main equipment used by the spinal surgical robot. (A) CT scanner, (B) C-arm fluoroscopes, (C) physician workstations and surgical robots. CT, computed tomography.

procedures:[1] Preoperative planning, where the surgeon employs the proprietary software to devise a surgical strategy based on preoperative CT scans; and intraoperative planning[2], in which a three-dimensional (3D) CT scan is acquired using an O-arm (Medtronic PLC, Medtronic Inc, Dublin, Ireland) with the array connected to the robotic arm.[37]

Following Medtronic's acquisition of the aforementioned company in 2018, the MAZOR X STEALTH EDITION™ was subsequently launched, amalgamating cutting-edge surgical planning software, 15 years of Mazor robotic guidance expertise, and a quarter-century of Stealth™ Navigation experience.[38] Consequently, the spinal surgery robot, with Mazor X as its core, has undergone a transformation from non-navigated to navigated. After the surgical planning scheme was designed, the two versions of the robot needed to complete a series of operations to place the screws. However, the Stealth system eliminates the need for a k-wire during tapping or screw placement. Upon positioning the robotic arm, real-time visualization of instrument is provided to navigate and implant them in relation to the preoperative plan position. The multicenter study conducted by Lee *et al* demonstrated that both robot systems attained high screw accuracy. Nevertheless, the Stealth system resulted in considerably reduced fluoroscopic radiation time, lower robot abandonment rates, and decreased blood transfusion rates compared to Mazor X.[39]

Mazor robotics is already a pretty standardized process, including transforaminal lumbar interbody fusion (TLIF), midline lumbar interbody fusion (MIDLIF), deformity procedure and so on. Many scholars have carried out research on the effect of this technology. O'Connor *et al.*'s technique note presents promising outcomes about the using of MAZOR X STEALTH EDITION™, revealing that the initial 90 pedicle screws placed using the Mazor X Stealth Edition robot achieved 100% grade A accuracy on the Gertzbein-Robbins scale and no complications were encountered in any of the cases.[40] Buza *et al.*'s study demonstrated the workflow of this robotic system placing the cortical-based trajectory (CBT) screws.[41] In the past two years, there has been more and more research on this robot, showing the encouraging results in different spinal surgery.[42,43]

TiRobot® and TiRobot II

TiRobot® is the first medical device-certified spinal surgical robot in China, designed to aid surgeon in accurate positioning for spine surgery and traumatic orthopedics. Following the release of TiRobot® in 2016, the enhanced TiRobot II was introduced in 2020, building upon the initial version. As of the first quarter of 2023, 170 units have been installed domestically, and the TiRobot Orthopedic Robotic System has been used in over 40,000 procedures.[44]

TiRobot share similarities in composition with Mazor spinal robots and are compatible with both 2D and 3D modes, including three functions: Space mapping, path planning and positioning. Utilizing an orthopedic guide and a unique intelligent algorithm for screw trajectory calculation, the robotic arm accurately moves to the planned position, offering surgeons a precise and stable trajectory. This enables surgeons to design and place internal implants as intended and the positioning accuracy of 0.8 mm can be achieved.

Since Tian *et al.* from Jishuitan Hospital performed a posterior C1–2 transarticular screw fixation and anterior odontoid screw fixation using this surgical robot in 2015,[45,46] the robot-assisted system has been employed for various spinal surgeries.[47–49]

The study conducted by Tian *et al.* revealed that the TiRobot® system considerably enhanced the precision and security of pedicle screw fixation without extending the surgical duration or exacerbating complications, indicating its substantial potential for clinical use.[50]

In their another investigation of the TiRobot II, their results demonstrated that robot-assisted pedicle screw placement surpasses free-hand methods in accuracy and TiRobot-assisted thoracolumbar pedicle screw placement is a reliable and safe technique [51].

Other robotic system

Robots like Globus Medical's ExcelsiusGPS® (Philadelphia, PA, USA) and the Rosa® (Indiana, IN, USA) spine robot aid spinal surgeons in performing precise screw placement. Fayed *et al.* confirmed the precision of percutaneous pedicle screws placement with ExcelsiusGPS (Philadelphia, PA, USA) robotic assistance in minimally invasive spinal fusion[52] and Lefranc *et al.* proved the precision of pedicle screw placement during lumbar arthrodesis performed with the ROSA (Indiana, IN, USA) Spine robot.[53]

Besides the aforementioned image navigation-integrated spinal robotic surgical assistance systems, the Da Vinci surgical robot (Sunnyvale, CA, USA), prevalent in general surgery, has been demonstrated to be apt for anterior lumbar interbody fusion a decade ago.[54]

ADVANTAGES AND DISADVANTAGES

Spinal surgery robots have emerged as a significant advancement in the field of spine surgery, offering numerous advantages and some disadvantages. This review provided a summary of the benefits and drawbacks associated with these robotic systems.

Advantages

Improved accuracy and decreased intraoperative errors

Spinal surgery robots enable greater precision in screw placement and trajectory planning and minimize the chances of intraoperative errors, leading to improved patient outcomes and reducing the risk of complications.[55,56]

Enhanced visualization

Robotic systems often incorporate 2D and 3D imaging technologies, providing surgeons with real-time intraoperative guidance, leading to better surgical outcomes.[57]

Reduced radiation exposure

The use of robotic systems in spinal surgery leads to decreased reliance on fluoroscopy, resulting in reduced radiation exposure for both patients and surgeons.[58]

Minimally invasive procedures

Robotic-assisted techniques facilitate minimally invasive procedures, which can lead to shorter hospital stays, less postoperative pain, and faster recovery times.[59]

Disadvantages

Cost

The high initial investment and maintenance costs of robotic systems may deter some hospitals and institutions from adopting the technology.[30]

Learning curve

Surgeons must undergo a steep learning curve to become proficient in the use of robotic systems, which can prolong surgical times initially.[60]

Limited applications

Spinal surgery robots may not be suitable for all types of spinal surgeries, and their efficacy in certain procedures is yet to be established.[61,62]

In conclusion, spinal surgery robots offer several advantages that can lead to improved patient outcomes and enhanced surgical precision. However, the high costs, learning curve, and limited applicability may deter some from adopting the technology.

CONCLUSION

This review encapsulates recent progress in the application of AI technologies, chiefly ML, DL, and surgical robotics, to spinal disease diagnosis, treatment, and surgery. The growing integration of AI in these areas underscores its potential for future development in spinal care. AI technology is increasingly used in spine research, which not only promotes the accuracy and intelligence of disease diagnosis and surgical implementation, but also provides a lot of convenience for the majority of spine radiologists, spine doctors and patients suffering from spinal diseases for a long time, and helps the development of medical career.

DECLARATION

Author Contributions

Hai Y and Zhang X contributed to conception and design of the study. Feng Z wrote the first draft of the manuscript. Yang H wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

Ethics Approval

Not applicable.

Source of Funding

This research received no external funding.

Conflict of Interest

Yong Hai and Xinuo Zhang are editorial board members of the journal. The article was subject to the journal's standard procedures, with peer review handled independently of the editor and the affiliated research groups.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author.

REFERENCES

1. Hamet P, Tremblay J. Artificial intelligence in medicine. *Metabolism*. 2017;69S:S36–S40.
2. Benzakour A, Altsitzioglou P, Lemée JM, Ahmad A, Mavrogenis AF, Benzakour T. Artificial intelligence in spine surgery. *Int Orthop*. 2023;47(2):457–465.
3. Hornung AL, Hornung CM, Mallow GM, *et al.* Artificial intelligence in spine care: current applications and future utility. *Eur Spine J*. 2022;31(8):2057–2081.
4. Elson DS, Cleary K, Dupont P, Merrifield R, Riviere C. Medical Robotics. *Ann Biomed Eng*. 2018;46(10):1433–1436.
5. Theodore N, Arnold PM, Mehta AI. Introduction: the rise of the robots in spinal surgery. *Neurosurg Focus*. 2018;45(VideoSuppl1):Intro.
6. Wang H, Tang ZR, Li W, *et al.* Prediction of the risk of C5 palsy after posterior laminectomy and fusion with cervical myelopathy using a support vector machine: an analysis of 184 consecutive patients. *J Orthop Surg Res*. 2021;16(1):332.
7. DeVries Z, Hoda M, Rivers CS, *et al.* Development of an unsupervised machine learning algorithm for the prognostication of walking ability in spinal cord injury patients. *Spine J*. 2020;20(2):213–224.
8. Wang H, Fan T, Yang B, Lin Q, Li W, Yang M. Development and Internal Validation of Supervised Machine Learning Algorithms for Predicting the Risk of Surgical Site Infection Following Minimally Invasive Transforaminal Lumbar Interbody Fusion. *Front Med (Lausanne)*. 2021;8:771608.
9. Dong S, Li W, Tang ZR, Wang H, Pei H, Yuan B. Development and validation of a novel predictive model and web calculator for evaluating transfusion risk after spinal fusion for spinal tuberculosis: a retrospective cohort study. *BMC Musculoskelet Disord*. 2021;22(1):825.
10. Wang KY, Suresh KV, Puvanesarajah V, Raad M, Margalit A, Jain A. Using Predictive Modeling and Machine Learning to Identify Patients Appropriate for Outpatient Anterior Cervical Fusion and Discectomy. *Spine (Phila Pa 1976)*. 2021;46(10):665–670.
11. Siccoli A, de Wispelaere MP, Schroder ML, Staartjes VE. Machine learning-based preoperative predictive analytics for lumbar spinal stenosis. *Neurosurg Focus*. 2019;46(5):E5.
12. Halicka M, Wilby M, Duarte R, Brown C. Predicting patient-reported outcomes following lumbar spine surgery: development and external validation of multivariable prediction models. *BMC Musculoskelet Disord*. 2023;24(1):333.
13. Xiong C, Zhao R, Xu J, *et al.* Construct and Validate a Predictive Model for Surgical Site Infection after Posterior Lumbar Interbody Fusion Based on Machine Learning Algorithm. *Comput Math Methods Med*. 2022;2022:2697841.
14. Mamlook REA, Wells LJ, Sawyer R. Machine-learning models for predicting surgical site infections using patient pre-operative risk and surgical procedure factors. *Am J Infect Control*. 2023;51(5):544–550.
15. Indolia S, Goswami AK, Mishra SP, Asopa P. Conceptual Understanding of Convolutional Neural Network—A Deep Learning Approach. *Procedia Computer Science*. 2018;132:679–688.
16. Ronneberger O, Fischer P, Brox T. U-net: Convolutional networks for biomedical image segmentation. In: *Medical Image Computing and Computer-Assisted Intervention—MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18*. Springer International Publishing; 2015: 234–241.
17. Alkadri S, Ledwos N, Mirchi N, *et al.* Utilizing a multilayer perceptron artificial neural network to assess a virtual reality surgical procedure. *Comput Biol Med*. 2021;136:104770.
18. Kónya S, Natarajan TS, Allouch H, Nahleh KA, Dogheim OY, Boehm H. Convolutional neural network-based automated segmentation and labeling of the lumbar spine X-ray. *J Craniovertebr Junction Spine*. 2021;12(2):136–143.
19. Das P, Pal C, Acharyya A, Chakrabarti A, Basu S. Deep neural network for automated simultaneous intervertebral disc (IVDs) identification and segmentation of multi-modal MR images. *Comput Methods Programs Biomed*. 2021;205:106074.
20. Alukaev D, Kiselev S, Mustafaev T, Ainur A, Ibragimov B, Vrtovec T. A deep learning framework for vertebral morphometry and Cobb angle measurement with external validation. *Eur Spine J*. 2022;31(8):2115–2124.
21. Ouyang H, Meng F, Liu J, *et al.* Evaluation of Deep Learning-Based Automated Detection of Primary Spine Tumors on MRI Using the Turing Test. *Front Oncol*. 2022;12:814667.
22. Mao L, Xia Z, Pan L, *et al.* Deep learning for screening primary osteopenia and osteoporosis using spine radiographs and patient clinical covariates in a Chinese population. *Front Endocrinol (Lausanne)*. 2022;13:971877.
23. Yeh LR, Zhang Y, Chen JH, *et al.* A deep learning-based method for the diagnosis of vertebral fractures on spine MRI: retrospective training and validation of ResNet. *Eur Spine J*. 2022;31(8):2022–2030.
24. Lee GW, Shin H, Chang MC. Deep learning algorithm to evaluate cervical spondylotic myelopathy using lateral cervical spine radiograph. *BMC Neurol*. 2022;22(1):147.
25. Lehnen NC, Haase R, Faber J, *et al.* Detection of Degenerative Changes on MR Images of the Lumbar Spine with a Convolutional Neural Network: A Feasibility Study. *Diagnostics (Basel)*. 2021;11(5):902.
26. Zhang B, Yu K, Ning Z, *et al.* Deep learning of lumbar spine X-ray for osteopenia and osteoporosis screening: A multicenter retrospective cohort study. *Bone*. 2020;140:115561.
27. Hallinan JTPD, Zhu L, Yang K, *et al.* Deep Learning Model for Automated Detection and Classification of Central Canal, Lateral Recess, and Neural Foraminal Stenosis at Lumbar Spine MRI. *Radiology*. 2021;300(1):130–138.
28. Saravi B, Zink A, Ülkümen S, Couillard-Despres S, Hassel F, Lang G. Performance of Artificial Intelligence-Based Algorithms to Predict Prolonged Length of Stay after Lumbar Decompression Surgery. *J Clin Med*. 2022;11(14):4050.
29. Kantelhardt SR, Martinez R, Baerwinkel S, Burger R, Giese A, Rohde V. Perioperative course and accuracy of screw positioning in conventional, open robotic-guided and percutaneous robotic-guided, pedicle screw placement. *Eur Spine J*. 2011;20(6):860–868.
30. Le X, Tian W, Shi Z, *et al.* Robot-Assisted Versus Fluoroscopy-Assisted Cortical Bone Trajectory Screw Instrumentation in Lumbar Spinal Surgery: A Matched-Cohort Comparison. *World Neurosurg*. 2018;120:e745–e751.
31. Wang JQ, Wang Y, Feng Y, *et al.* Percutaneous Sacroiliac Screw Placement: A Prospective Randomized Comparison of Robot-assisted Navigation Procedures with a Conventional Technique. *Chin Med J (Engl)*. 2017;130(21):2527–2534.
32. D'Souza M, Gendreau J, Feng A, Kim LH, Ho AL, Veeravagu A. Robotic-Assisted Spine Surgery: History, Efficacy, Cost, And Future Trends. *Robot Surg*. 2019;6:9–23.
33. Overley SC, Cho SK, Mehta AI, Arnold PM. Navigation and Robotics in Spinal Surgery: Where Are We Now? *Neurosurgery*. 2017;80(3S):S86–S99.
34. Lee NJ, Leung E, Buchanan IA, *et al.* A multicenter study of the 5-year trends in robot-assisted spine surgery outcomes and complications. *J Spine Surg*. 2022;8(1):9–20.

35. Rajasekaran S, Vidyadhara S, Ramesh P, Shetty AP. Randomized clinical study to compare the accuracy of navigated and non-navigated thoracic pedicle screws in deformity correction surgeries. *Spine (Phila Pa 1976)*. 2007;32(2):E56–E64.
36. Elie Massaad, Ganesh M Shankar, John H Shin. Novel Applications of Spinal Navigation in Deformity and Oncology Surgery-Beyond Screw Placement. *Oper Neurosurg (Hagerstown)*. 2021;21(Supp 1):S23–S38.
37. Khan A, Meyers JE, Siasios I, Pollina J. Next-Generation Robotic Spine Surgery: First Report on Feasibility, Safety, and Learning Curve. *Oper Neurosurg (Hagerstown)*. 2019;17(1):61–69.
38. Medtronic Corp. Mazor X Stealth Edition. Accessed August 20, 2023. https://www.medtronic.com/us-en/healthcare-professionals/products/spinalorthopaedic/spine-robotics/mazor-x-stealth-edition.html
39. Lee NJ, Zuckerman SL, Buchanan IA, *et al.* Is there a difference between navigated and non-navigated robot cohorts in robot-assisted spine surgery? A multicenter, propensity-matched analysis of 2,800 screws and 372 patients. *Spine J*. 2021;21(9):1504–1512.
40. O'Connor TE, O'Hehir MM, Khan A, *et al.* Mazor X Stealth Robotic Technology: A Technical Note. *World Neurosurg*. 2021;145:435–442.
41. Buza JA 3rd, Good CR, Lehman RA Jr, *et al.* Robotic-assisted cortical bone trajectory (CBT) screws using the Mazor X Stealth Edition (MXSE) system: workflow and technical tips for safe and efficient use. *J Robot Surg*. 2021;15(1):13–23.
42. Good CR, Orosz LD, Lehman RA, Gum JL, Fox D, Lieberman IH. Minimally Invasive Posterior Facet Decortication and Fusion Using Navigated Robotic Guidance: Feasibility and Workflow Optimization. *Neurospine*. 2022;19(3):773–779.
43. Schwendner M, Meyer B, Krieg SM. [Robot-assisted pedicle screw placement]. *Oper Orthop Traumatol*. 2023;35(1):37–42.
44. Tinavi Corp. TiRobot. Accessed August 20, 2023. http://en.tinavi.com/
45. Tian W, Wang H, Liu YJ. Robot-assisted Anterior Odontoid Screw Fixation: A Case Report. *Orthop Surg*. 2016;8(3):400–404.
46. Wei Tian. Robot-Assisted Posterior C1–2 Transarticular Screw Fixation for Atlantoaxial Instability: A Case Report. *Spine (Phila Pa 1976)*. 2016;41 Suppl 19:B2–B45.
47. Lin S, Tang LY, Wang F, Yuan XW, Hu J, Liang WM. TiRobot-assisted percutaneous kyphoplasty in the management of multilevel (more than three levels) osteoporotic vertebral compression fracture. *Int Orthop*. 2023;47(2):319–327.
48. Zhu ZD, Xiao CW, Tan B, *et al.* TiRobot-Assisted Percutaneous Cannulated Screw Fixation in the Treatment of Femoral Neck Fractures: A Minimum 2-Year Follow-up of 50 Patients. *Orthop Surg*. 2021;13(1):244–252.
49. Ge S, Zhang L, Zhou Z, Jia S, Zheng L. [TiRobot-assisted surgery by O-arm navigation system for percutaneous minimally invasive treatment of posterior pelvic ring injury]. *Zhongguo Xiu Fu Chong Jian Wai Ke Za Zhi*. 2022;36(8):934–939.
50. Tian W, Fan M, Han X, Zhao J, Liu Y. Pedicle screw insertion in spine: a randomized comparison study of robot-assisted surgery and fluoroscopy-guided techniques. *J Clin Orthop Res*. 2016;1(1):4–10.
51. Yan K, Zhang Q, Tian W. Comparison of accuracy and safety between second-generation TiRobot-assisted and free-hand thoracolumbar pedicle screw placement. *BMC Surg*. 2022;22(1):275.
52. Fayed I, Tai A, Triano M, *et al.* Robot-Assisted Percutaneous Pedicle Screw Placement: Evaluation of Accuracy of the First 100 Screws and Comparison with Cohort of Fluoroscopy-guided Screws. *World Neurosurg*. 2020;143:e492–e502.
53. Chenin L, Capel C, Fichten A, Peltier J, Lefranc M. Evaluation of Screw Placement Accuracy in Circumferential Lumbar Arthrodesis Using Robotic Assistance and Intraoperative Flat-Panel Computed Tomography. *World Neurosurg*. 2017;105:86–94.
54. Beutler WJ, Peppelman WC Jr, DiMarco LA. The da Vinci robotic surgical assisted anterior lumbar interbody fusion: technical development and case report. *Spine (Phila Pa 1976)*. 2013;38(4):356–363.
55. Devito DP, Kaplan L, Dietl R, *et al.* Clinical acceptance and accuracy assessment of spinal implants guided with SpineAssist surgical robot: retrospective study. *Spine (Phila Pa 1976)*. 2010;35(24):2109–2115.
56. Florian Ringel, Carsten Stüer, Andreas Reinke, *et al.* Accuracy of robot-assisted placement of lumbar and sacral pedicle screws: a prospective randomized comparison to conventional freehand screw implantation. *Spine (Phila Pa 1976)*. 2012;37(8):E496–E501.
57. Naureen Keric, Christian Doenitz, Amer Haj, *et al.* Evaluation of robot-guided minimally invasive implantation of 2067 pedicle screws. *Neurosurg Focus*. 2017;42(5):E11.
58. Kim HJ, Jung WI, Chang BS, Lee CK, Kang KT, Yeom JS. A prospective, randomized, controlled trial of robot-assisted vs freehand pedicle screw fixation in spine surgery. *Int J Med Robot*. 2017;13(3):10.
59. Ghasem A, Sharma A, Greif DN, Alam M, Maaieh MA. The Arrival of Robotics in Spine Surgery: A Review of the Literature. *Spine (Phila Pa 1976)*. 2018;43(23):1670–1677.
60. Pennington Z, Judy BF, Zakaria HM, *et al.* Learning curves in robot-assisted spine surgery: a systematic review and proposal of application to residency curricula. *Neurosurg Focus*. 2022;52(1):E3.
61. Zhou LP, Zhang ZG, Li D, *et al.* Robotics in Cervical Spine Surgery: Feasibility and Safety of Posterior Screw Placement. *Neurospine*. 2023;20(1):329–339.
62. Urakov TM, Chang KH, Burks SS, Wang MY. Initial academic experience and learning curve with robotic spine instrumentation. *Neurosurg Focus*. 2017;42(5):E4.