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Artificial intelligence: a new cutting-edge tool in spine surgery

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The purpose of this narrative review was to comprehensively elaborate the various components of artificial intelligence (AI), their applications in spine surgery, practical concerns, and future directions. Over the years, spine surgery has been continuously transformed in various aspects, including diagnostic strategies, surgical approaches, procedures, and instrumentation, to provide better-quality patient care. Surgeons have also augmented their surgical expertise with rapidly growing technological advancements. AI is an advancing field that has the potential to revolutionize many aspects of spine surgery. We performed a comprehensive narrative review of the various aspects of AI and machine learning in spine surgery. To elaborate on the current role of AI in spine surgery, a review of the literature was performed using PubMed and Google Scholar databases for articles published in English in the last 20 years. The initial search using the keywords "artificial intelligence" AND "spine," "machine learning" AND "spine," and "deep learning" AND "spine" extracted a total of 78, 60, and 37 articles and 11,500, 4,610, and 2,270 articles on PubMed and Google Scholar. After the initial screening and exclusion of unrelated articles, duplicates, and non-English articles, 405 articles were identified. After the second stage of screening, 93 articles were included in the review. Studies have shown that AI can be used to analyze patient data and provide personalized treatment recommendations in spine care. It also provides valuable insights for planning surgeries and assisting with precise surgical maneuvers and decision-making during the procedures. As more data become available and with further advancements, AI is likely to improve patient outcomes.

Keywords: Artificial intelligence; Machine learning; Spine; Technology; Decision-making

Introduction

Over the past few decades, a dramatic transition has occurred in spine surgery. Surgeons have evolved from performing open to performing minimally invasive tubular and endoscopic surgeries to provide better patient outcomes with minimal trauma to the internal environment. Parallel advancements have also progressed in medical research and research tools. Medical research involves data analysis of various dimensions. However, the availability of vast amounts of data prevents data-driven methods from translating into clinically relevant models [1]. Artificial intelligence (AI) is emerging as a critical tool in the assessment of diverse healthcare data.

Machine learning (ML) algorithms, a subtype of AI, can be used to analyze patient-related data and suggest strategies that would help clinicians during treatment. Spine surgeries have their set of risks and complications, and the information and assistance provided by AI could help surgeons avoid minor to catastrophic adverse events in patient care. Several authors have examined the effect of AI in specialties such as radiology, oncology, primary care, and basic sciences, and reports suggest favorable prospects for AI [2-4]. Thus, this narrative review aimed to briefly discuss the applications of AI in spine surgery and its future directions.

Literature search

An elaborate search was performed using the following keywords: “artificial intelligence” AND “spine,” “machine learning” AND “spine,” “deep learning” AND “spine” on PubMed and Google Scholar (scholar.google.com) on August 10, 2023. Crucial questions and research regarding AI in spine surgery were identified, and relevant articles on these topics were included.

Results

The initial search using the keywords “artificial intelligence” AND “spine,” “machine learning” AND “spine,” and “deep learning” AND “spine” extracted a total of 78, 60, and 37 articles and 11,500, 4,610, and 2,270 articles on PubMed and Google Scholar, respectively. In the initial screening, articles unrelated to AI, duplicate articles, and non-English articles were excluded based on the abstracts or titles of the articles. This initial screening resulted in the identification of 405 articles. Complete manuscripts were obtained for all selected articles and thoroughly scrutinized during the second stage of article selection. All articles not concerning the AI application in spine surgery, articles regarding AI in other medical specialties, articles not on the concerned questions, and non-English articles were excluded. Randomized controlled trials, level 1 studies, and review articles were preferred (Fig. 1). Finally, 93 articles were included in this review. Screening for the included articles based on Preferred Reporting Items for Systematic Reviews and Meta-Analyses or Methodological Index for Nonrandomized studies criteria was not performed.

AI and its components in medicine

In medicine, AI seeks to emulate the characteristics of human intelligence, such as learning, communication, decision-making, and adaptation to changing environments in a clinical setting. Thus, it includes

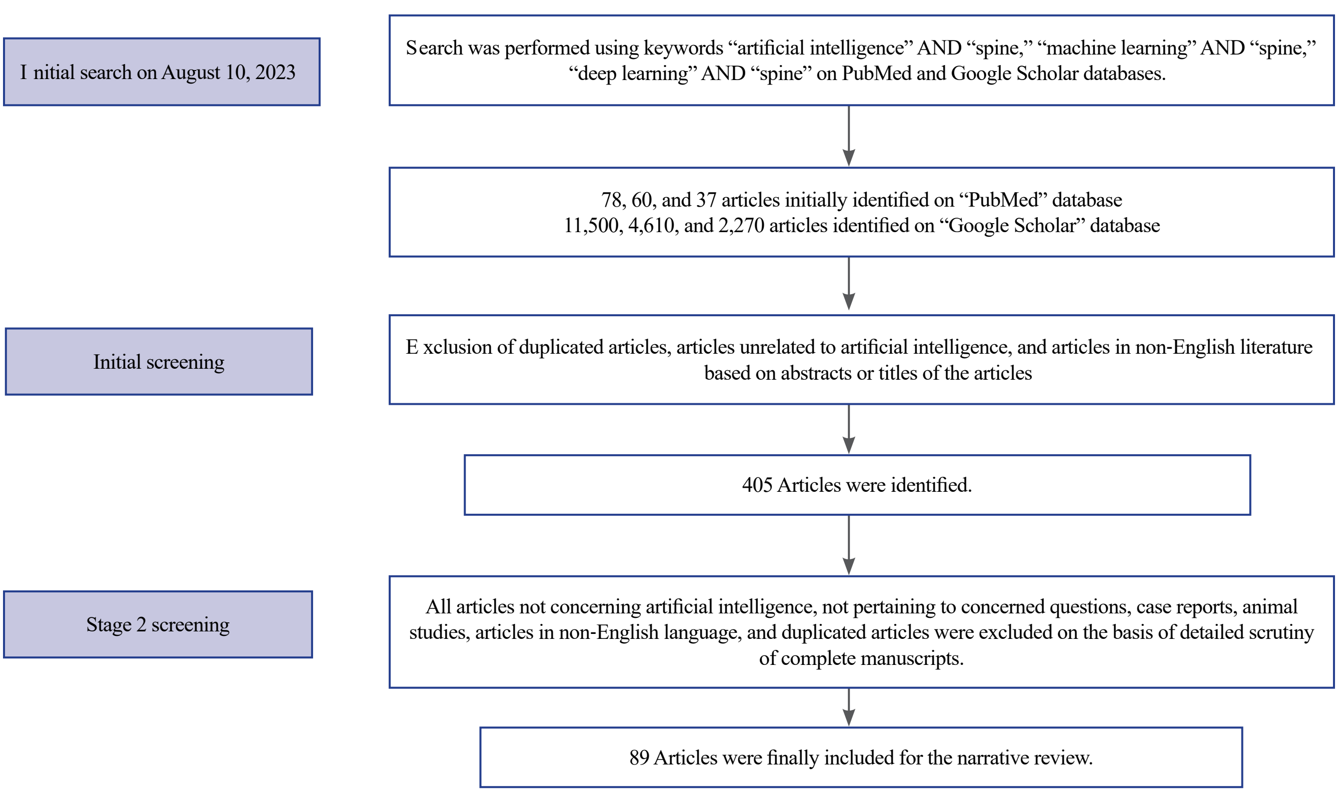

Fig. 1. Flowchart depicting the methodology of article selection.

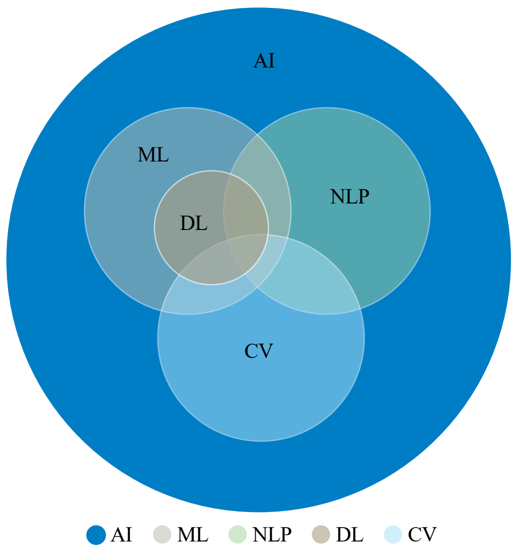

Fig. 2. Various domains which are the integral parts of artificial intelligence (AI) in medical field. ML, machine learning; NLP, natural language processing; DL, deep learning; CV, computer vision.

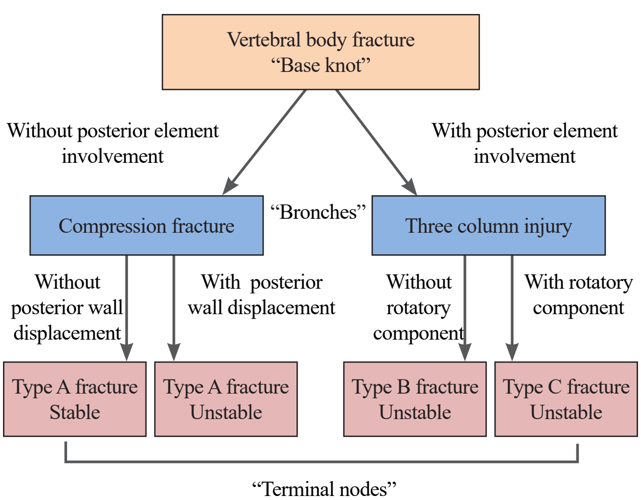

Fig. 3. Decision tree model of artificial intelligence (AI) showing AO classification of thoracolumbar fractures in their algorithm. As shown, it has a base knot, branches and terminal nodes.

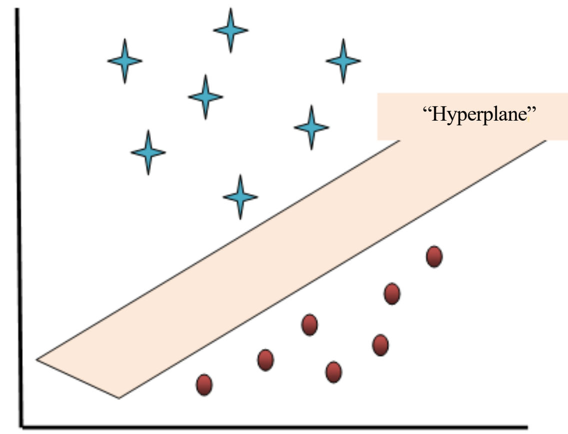

Fig. 4. In a basic two dimensional support vector machine algorithm, data points are classified on either side of the decision boundary. The decision boundary is termed "hyperplane."

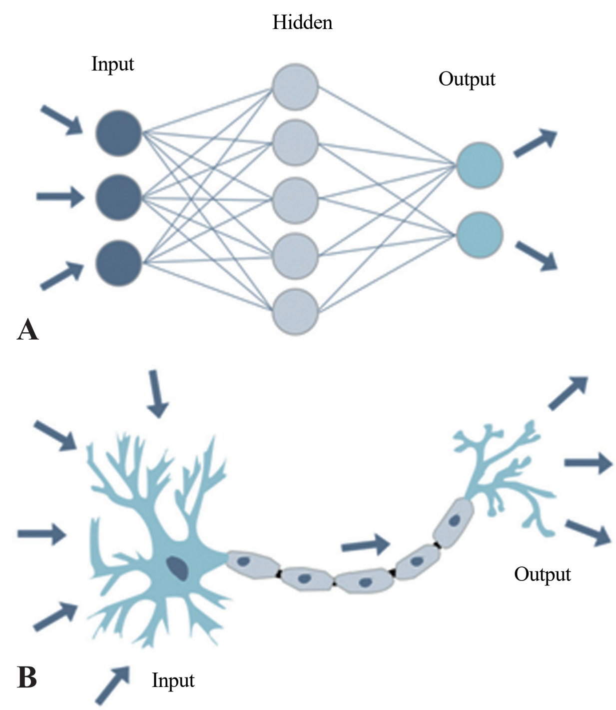

Fig. 5. (A) Shows the framework in an artificial neural network (ANN). The input data passes through numerous hidden networks to arrive at an output. **(B)** Human neuronal structure which is the basis of ANN network. The input is passed from dendrites to the cell body and through myelinated axons to the synape/adjacent neuron.

diverse domains, of which ML is of particular interest and has major applicability in medicine (Fig. 2). ML is a subset of AI that uses computational models to learn large complex data and generate useful predictive outputs without any explicit programing. The fundamental principles of ML are based on intricate statistical and mathematical optimization using numerical data [5]. Decision tree learning, support vector machines (SVMs), and artificial neural networks (ANNs) are three common ML models. These models are based on supervised learning methodologies in which the machine is trained to predict the outputs based on previously collected inputs for which the outputs are known; hence, a "labeled" dataset is used [6]. A decision tree is a graphical representation technique that provides a visual depiction of various decisions with the base knot and various branches attached to the knot and ending in terminal nodes (Fig. 3). Because of their peculiar structure, they are easier to interpret by clinicians. The SVM is adapted for nonlinear classification and regression, considering each input as a multidimensional vector. SVM algorithms incorporate decision boundaries called hyperplanes (Fig. 4). In spine pathologies, disk degeneration grading and identification of the type of scoliotic curves can be performed using SVM algorithms. In the ANN model, the machine integrates data using the linkage of artificial neurons. The information flows through several layers of the hidden neuronal network; finally, the processed output is generated (Fig. 5). This ANN multilayered strategy is also known as "deep learning" [7]. Other AI tools include natural language processing (NLP) and computer vision [8]. NLP involves mining and analyzing text-based data that can be incorporated into analytic algorithms [9]. In simple terms, NLP quickly extracts patient data from electronic records, including lifestyle and several other health determinants that could otherwise be cumbersome for human evaluation. Computer vision is another advanced tool that aids in the evaluation and processing of patient imaging data with higher precision and clarity. It often uses convoluted ANN pathways for image segmentation and analysis. U-Net is an example of these networks that are primarily used in neurosurgical imaging [10].

By using these specialized tools, AI facilitates and augments patient healthcare by assisting clinicians in four important aspects: diagnosis (provides inference based on patient data including signs, symptoms, and investigations), therapy (aids in surgical decision-making and enhancing postoperative patient care), prognosis (enables the surgeon to predict patient-specific outcomes and modify treatment strategies), and research (with the available patient data, AI can enhance complex statistical analysis to innovative ideas and research in spine care).

Diagnosis of spinal ailments with AI

Numerous studies in AI regarding various aspects of low back pain have been published [11-14], especially disk-related pathologies. Reports have shown that factors such as disk degeneration, endplate defects, Modic changes, and vertebral osteoarthritis can be automatically detected in magnetic resonance imaging using AI algorithms such as SVMs and ANNs [15-18]. "Segmentation" of medical images to provide pixel-specific data has been an important contribution of computer vision in spinal imaging [19]. Gong et al. [20] proposed a network framework called "Axial-SpineGAN" for simultaneous segmentation and diagnosis of spinal structures using axial magnetic resonance imaging (MRI). Recently, magnetic resonance (MR) image augmentation using an ANN was approved by the Federal Drug Administration [21]. This technology facilitates MRI in a fraction of the normal study time, and the proposed benefits include improved patient satisfaction, enhanced image quality, and fewer motion artifacts. Regarding disk degeneration, the Pfirmann grading system has been validated in multiple studies; however, few authors have reported interobserver variability and heterogeneity in the results obtained using this grading system [22,23]. ML tools such as convoluted neural networks (CNNs) and deep learning can extract "radiomic data" from MR images that are quite difficult to interpret by visual inspection with the naked eye, and studies have shown an accuracy of 97% in assessing disk degeneration [24]. Salient features such as the shape and intensity of the disks can be evaluated in detail using the feature-extraction technique and critically analyzed [25]. Similarly, texture analysis of ligamentous structures in spinal MRI produced parameters for more accurate detection of lumbar canal stenosis [26]. Won et al. [27] compared the efficacy of grading lumbar canal stenosis in axial MRI between radiology experts and trained CNN, and the final agreement rates of decision-making among them were 77.9% and 74.9%, respectively, which were not significant. Other transformative innovations of AI in diagnostic imaging include MR fingerprinting and the identification of tissue properties using synthetic MRI. These techniques can be useful for the preoperative assessment of osteoporosis and early detection of spondyloarthropathies [28,29]. Apart from MRI, AI also has implications in the evaluation of plain radiographs [30,31] and computed tomography scans [32,33].

ML models, such as regression SVM and deep ANN, were adopted for calculating Cobb's angle in patients with scoliosis and yielded satisfactory results with an error rate of <3° [34,35]. Lyu et al. [36] incorporated a neural networking algorithm in a three-dimensional (3D) ultrasound scan to detect the best quality image for detecting the deformity and reported an accuracy of 100%. Jaremko et al. [37] studied 18 testing samples using a three-layered back-propagation ANN to estimate Cobb's angle in laser scan images of patients with deformity. They observed that the ANN of full torso imaging could distinguish Cobb's angle >30° with acceptable sensitivity and specificity [37]. These computer-aided systems, by their automated measurements, provide reliable and objective assessments of the deformity.

Recently, Zhu et al. [38] collected data from 775 patients who underwent cervical spine surgery and screened 84 patient variables to identify differences be-

Table 1. The studies available in the literature regarding the application of AI and ML algorithms in the diagnosis of LBP due to IVD degeneration

Author	Year	Journal	AI model	Aim of the study	Results
Sanders et al. [41]	2000	*Computers in Biology and Medicine*	Feedforward NN	LBP diagnosis	Using the more complex DGA regions as inputs resulted in a significantly better sensitivity
Huber et al. [26]	2009	*European Journal of Radiology*	ML algorithms	To compare the reproducibility and accuracy of texture analysis in the detection and grading of lumbar stenosis in MR imaging	Tested several machine learning algorithms for the lumbar spinal stenosis grading on 82 patients, showed moderate reproducibility
Alomari et al. [42]	2010	*International Journal of Computer Assisted Radiology and Surgery*	Probabilistic Gibb's model	Disc degeneration-detection of abnormal discs from clinical T2-weighted MR images	Achieved over 91% abnormality detection accuracy in a cross-validation experiment with 80 clinical cases
Sari et al. [12]	2010	*Journal of Medical Systems*	ANN, ANFIS	To predict the intensity of LBP	Effective to predict the pain intensity level objectively
Alomari et al. [43]	2011	*International Journal for Computer Assisted Radiology and Surgery*	CAD system	For diagnosis of disc herniation based on segmentation of the discs from T2-SPIR sagittal MRI images and extraction of suitable shape features	An average 92.5% herniation diagnosis accuracy was observed in a cross-validation experiment with 65 clinical cases
Ghosh et al. [44]	2011	*IEEE*	HOG, SVM	To diagnose LBP	99% disc localization accuracy in MRI
Koh et al. [45]	2012	*International Journal of Computer-Assisted Radiology and Surgery*	SVM	Computer-aided framework for diagnosis of disc herniation in MRI	Successful detection of disc herniation with 99% accuracy, achieving a speedup factor of 30 in comparison with radiologists
Parsaeian et al. [46]	2012	*Iranian Journal of Public Health*	ANN	To compare the ability of ANN with logistic regression in the prediction of LBP	When complex dependencies and interactions exist in the dataset, ANN may be the best choice over logistic regression.
Oktay et al. [47]	2014	*Comp Med Imaging Graph*	SVM	For the automated diagnosis of degenerative IDD in mid-sagittal MR images	Computer-aided diagnosis of degenerative IVD is comparable to the state of art
Ruiz-Espana et al. [48]	2015	*Computers in Biology and Medicine*	Vector flow algorithm	Computer-aided diagnosis for detection and classification of lumbar spine disease in MRI	Achieving accuracies greater than 90% in 67 patients.
Nikravan et al. [49]	2016	*Biomedical Engineering: Applications, Basis, Communications*	SVM, ANN	Automatic diagnosis of LDH	92.38% and 93.80% accuracy for ANN and SVM classifiers, respectively
Oyedotun et al. [50]	2016	*Technology and Health Care*	Feedforward NN	Automatic system to recognize disc hernia and spondylolisthesis using biomechanical features and NN.	NNs can be as efficient and effective as expert systems for the diagnosis of disc hernia and listhesis.
Ashouri et al. [51]	2017	*Computers in Biology and Medicine*	SVM	Inertial sensors in conjugation with pattern recognition techniques for LBP diagnosis	A single inertial sensor can identify LBP with a sensitivity of 100% and accuracy of 92%.
Jamaludin et al. [52]	2017	*European Spine Journal*	CNN	Automation of radiological features from MRIs of the lumbar spine.	The detection system achieved 95.6% accuracy in terms of disc detection and labelling.
Beulah et al. [17]	2018	*Multimedia Tools and Application*	HOG, SVM	To identify the disc bulge in axial lumbar spine MR images	An accuracy of 92.8% for classifying normal and bulge, compared with classifiers such as K-NN, DT, and feed-forward NN
Ebrahimzadeh et al. [53]	2018	*Biomed Engineering: Applications, Basis, Communications*	MLP, K-NN, SVM	For automatic diagnosis of LDH based on clinical MRI data	Demonstrated 91.90%, 92.38%, and 95.23% accuracy for ANN, K-NN, and SVM classifiers, respectively
Ebrahimzadeh et al. [54]	2018	*Medlife open access*	ANN	LDH in MRI	The results revealed an accuracy of 96.38% for ANN and 97.80% for SVM, respectively.
Han et al. [55]	2018	*Neuroinformatics*	DMML-Net	To diagnose foraminal stenosis in MRI	DMML-Net achieves high performance (0.845 mean average precision)
Hu et al. [56]	2018	*Ergonomics*	DNN	Human balance and body sway performance were applied in LBP diagnosis	LBP patients were identified with a precision of 97.2% in static standing.

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Table 1. Continued

Author	Year	Journal	AI model	Aim of the study	Results
Lee et al. [57]	2019	*Pain*	SVM	A multivariate ML model that learns from central and autonomic features, and then classifies clinical pain states and predicts pain intensity	Exacerbation of LBP in patients showing an increase of cerebral blood flow in the thalamus, prefrontal and posterior cingulate cortices, and an increment of heart rate variability with an accuracy of 92.5%
Salehi et al. [58]	2019	*Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science*	SVM+K-NN	To diagnose disc herniation by processing T1- and T2-weighted sagittal MRI	Demonstrated an average of 97.9% and 97.1% accuracy with cross-validation method using KNN and linear SVM, respectively
Shen et al. [59]	2019	*NeuroImage: Clinical*	SVM	To investigate the resting state functional connectivity changes of visual networks in cLBP patients and the feasibility of distinguishing cLBP patients from healthy controls using ML methods	The resting state functional connectivity of the visual network could achieve a classification accuracy of 79.3% in distinguishing cLBP patients from HCs.
Varcin et al. [60]	2019	*International Artificial Intelligence and Data Processing Symposium*	ANN	Diagnosis of spondylolisthesis by using two ANN AlexNet and GoogleLeNet	GoogleLeNet is 93.9 % accurate and performs slightly better than AlexNet (accuracy: 91.7%).
Zhao et al. [61]	2019	*Medical Image Analysis*	CNN	FAR network to perform spondylolisthesis grading by detecting critical vertebrae in MRI	FAR network is evaluated to be accurate and robust in spondylolisthesis grading.
Abdollahi et al. [62]	2020	*Sensors*	SVM, MLP	To develop a sensor-based ML model to classify nonspecific LBP patients into subgroups according to quantitative kinematic data	Accuracy levels of approximately 75% and 60% were achieved for SVM and MLP, respectively.
Gao et al. [63]	2020	*Journal of Magnetic Resonance Imaging*	DL models	Feasibility and improvement of a computer-assisted IVD degeneration grading in MRI based on the proposed PPR strategy	Accuracies of grade II and III IVD classification were improved by more than 10%, and the overall accuracy (grades I to V) was improved by over 8%.
Ketola et al. [64]	2020	*Journal of Orthopaedic Research*	ML algorithms	To investigate if more specific MRI predictors of LBA could be found via texture analysis and ML.	Best classification results were observed applying texture analysis to the two lowest IVD (L4–L5 and L5–S1), with a sensitivity of 82%, NPV of 94%, precision of 56%.
Kim et al. [11]	2020	*Healthcare Informatics Research*	CNN	To aid in the diagnosis of LBA using CT scan imaging	The proposed CNN approach achieved an average dice coefficient of 90.4%, a precision of 96.81%, and an F1 score of 91.64%.
Lewandrowski et al. [65]	2020	*International Journal of Spine Surgery*	DCNN and NLP	Lumbar disc degeneration and stenosis in MRI	Validation accuracy for foramina stenosis: 81%, central stenosis: 86.2%, and disc herniation: 85.2% respectively
Lewandrowski et al. [66]	2020	*International journal of spine surgery*	DL NN (RadBot) and NLP	Lumbar disc degeneration, canal stenosis in MRI	Overall positive predictive value: 80.3%, negative predictive value: 83.7%
Liew et al. [67]	2020	*European Spine Journal*	Functional data boosting	Predictive performance of statistical models which distinguishes different LBA using electromyography and kinematic variables, during low-load lifting	The most influential predictor was the biceps femoris muscle, the deltoid muscle, and the iliocostalis muscle.
Sundarsingh et al. [68]	2020	*International Journal of Imaging Systems and Technology*	HOG, LS-RBRP, RF	To diagnose desiccated and bulged IVD automatically by combining shape features	Performance analysis projects that the RF with HOG+LS-RBRP has an overall better accuracy of 94.7%.
Sustersic et al. [69]	2020	*Computers in Biology and Medicine*	DL algorithms	To investigate the best methodology for disc hernia diagnosis using foot force measurements.	Two algorithms with the highest accuracy were the Decision Tree and Naive Bayes methods.
Won et al. [27]	2020	*Spine*	DCNN	To identify lumbar spinal stenosis grading from MRI and compare it with expert opinion	Grading agreement between the experts was 77.5% and 75% in terms of accuracy and F1 scores.

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Table 1. Continued

Author	Year	Journal	AI model	Aim of the study	Results
Beulah et al. [70]	2021	*The Visual Computer*	SVM	To automatically diagnose degenerative discs from T2-weighted sagittal MR image	The patient-based analysis was performed and obtained an accuracy of 92.86%.
Hallinan et al. [71]	2021	*Radiology*	CNN	Lumbar stenosis in MRI	DL model is reliable with the classification of stenosis as the central canal (96.3% specificity), lateral recess (92.2% sensitivity), and neural foraminal (97.9% specificity).
Lamichhane et al. [72]	2021	*NeuroImage: Clinical*	SVM	Morphological changes in cerebral cortical thickness and resting-state functional connectivity measures as potential brain biomarkers for LBP.	An SVM trained using cortical thickness to classify LBP subjects from HC achieved an average classification accuracy of 74.51%, AUC=0.787 (95% CI, 0.66–0.91).
Lehnen et al. [73]	2021	*Diagnostics*	CNN	Detection of degenerative changes in MR imaging	100% accuracy for disc detection and labeling, 87% for disc herniations, and 98% for spinal canal stenosis
Pan et al. [74]pain in the lower limbs, and lower back pain. Magnetic resonance (MR	2021	*JMIR Med Inform*	DCNN	To diagnose disc bulge and disc herniation using MRI	Diagnostic efficiency and standardization of diagnosis reports can be significantly improved using the algorithm.
Tsai et al. [75]	2021	*Frontiers*	CNN	To automatically detect LDH in MR imaging	Overall, the highest mean average precision was 92.4%.
Su et al. [76]	2022	*Frontiers in endocrinology*	ResNet-50 framework	Lumbar spine pathology in MRI	Overall accuracy of grading LDH, LCCS, and LNRC were 84.2%, 86.9% and 81.2% respectively.
Phan [77]	2023	*International Journal of Health and Pharmaceutical Medicine*	Back propagation NN and fuzzy NN algorithms	LDH in MRI	Diagnosis rate of LDH is close to 96.2%, with an average error of 0.07.
Zhang et al. [78]	2023	*JOR Spine*	R-CNN	Diagnostic model for automated LDH detection and classification on lumbar axial T2-weighted MR images	AUC for model classification was 0.97 and 0.92 in the internal and external test datasets, respectively.

AI, artificial intelligence; ML, machine learning; LBP, low back pain; IVD, intervertebral disc; NN, neural network; DGA, dermatomes and gross anatomic; MR, magnetic resonance; ANN, artificial neural network; ANFIS, adaptive neuro-fuzzy inference system; CAD, computer-aided design; T2-SPIR, T2-spectral presaturation with inversion recovery; MRI, magnetic resonance imaging; HOG, histogram of oriented gradients; SVM, support vector machine; IDD, intervertebral disc descriptor; LDH, lumbar disc herniation; CNN, convoluted neural network; K-NN: K-nearest neighbor; DT, Decision Trees; MLP, multi-layer perceptron; DMML-Net, deep multiscale multitask learning network; DNN, deep neural network; cLBP, chronic low back pain; HC, healthy control; FAR, faster adversarial recognition; DL, deep learning; PPR, push-pull regularization; LBA, low back ache; NPV, negative predictive value; CT, computed tomography; DCNN, deep convoluted neural network; NLP, natural language processing; LS-RBRP, local sub-rhombus binary relation pattern; RF, random forest; AUC, area under the receiver operating characteristic curve; CI, confidence interval; LCCS, lumbar central canal stenosis; LNRC, lumbar nerve roots compression.

tween patients with positive and negative cervical ossification of the posterior longitudinal ligament (OPLL). They proposed an ML-driven nomogram to predict patients with cervical OPLL and could identify the risk factors and other associated characteristics of cervical OPLL. A few researchers have also developed computer-aided detection systems for the automated detection of spinal metastatic lesions in the thoracolumbar spine [39,40]. With more improvements in AI technology, the future could be automated reporting of radiological investigations, saving time and providing optimal results comparable with human reporting. Existing studies on the diagnosis of lumbar disk degeneration are shown in Table 1 [41-78].

AI-driven perioperative approach

AI allows for the comprehensive study of patient-specific anatomy and anatomical variations and the implementation of individualized surgeries. Lateral access lumbar spine surgeries have been on a rising trend, particularly in adult spinal deformities, owing to the magnitude of deformity correction they offer in both coronal and sagittal planes. However, complications such as lumbar plexus injury and ureteric and visceral injuries are a concern because of the narrow safety corridor. AI-enhanced ultrasound imaging was developed by Carson et al. [79] for the identification of internal and adjacent neural structures in lateral lumbar fusion surgeries, and the reported accuracy of nerve detection was >95%. Other recent advances such as robotic and navigation-guided procedures have revolutionized spine and spinal cord surgeries with their three-dimensional, real-time, and haptic feedback mechanisms. The Da Vinci Surgical System (Intuitive Surgical, Sunnyvale, CA, USA), SpineAssist (MAZOR Robotics Inc., Caesarea, Israel), ROSA (Medtech SA, Montpellier, France), and Excelsius GPS Robot (Globus Medical Inc., Audubon, PA, USA) are the commonly available surgical robots (Fig. 3). Studies have reported excellent outcomes with robotics in pedicle screw insertion, tumor excision, and spinal deformity correction surgeries [80,81]. In addition to their role in complex and challenging spine procedures, robots have been reported to be very useful in targeted procedures such as radiofrequency ablation, biopsy, and vertebral augmentation (kyphoplasty/vertebroplasty) [82]. AI-powered robots would be augmented with various DL and computer vision sensors (vision devices such as two-dimensional/3D cameras, fine tactile/vibration, proximity sensors, accelerometers, and other environmental sensors) that feed them with sensing data that they could analyze and act upon in real-time. These systems provide enhanced dexterity, precision, and stability during surgeries, allowing surgeons to perform complex operations with greater accuracy. However, the integration of AI algorithms in robotic navigation is still in its early stages and will gain much more prominence in the years to come.

Opioids are important rescue analgesics in spine surgery. More importantly, opioid therapy requires vigilant supervision, particularly in the older population, as it can induce dependence and cause adverse events following long-term use. Karhade et al. [83] proposed an AI-based model to stratify patients at risk of opioid dependence. Using this model, surgeons can identify at risk patients and adapt alternate pain management strategies, thereby mitigating the risks associated with opioid use [83]. Recently, Ayling et al. [84] examined the adverse events following lumbar spine surgeries for degenerative pathologies and reported that approximately 2.4% and 19.2% of patients had one of the major or minor perioperative adverse events, respectively. These adverse events not only increase hospitalization costs but also significantly affect surgical outcomes. Studies using the random forest approach to predict perioperative complications in adult spinal deformity surgery showed an accuracy of prediction of 87.6% [85]. Similarly, Wang et al. [86] employed a risk-stratification tool using ANNs in 12,492 patients to identify candidates who might be safe for ambulatory anterior cervical discectomy and fusion surgery, thereby reducing the chances of prolonged hospitalization. In addition, AI has been successfully evaluated to plan the discharge of patients following elective spine surgeries. The application of such algorithms would not only guide surgeons but also help patients reduce their healthcare costs and improve patient satisfaction.

Predictive and prognostic analytics using AI

Many prognostic tools are available in spine literature and are widely used in practice for the grading and prognosis of spinal disorders. Evaluating and analyzing these data and scoring systems for a larger population can be challenging for clinicians who use traditional statistical methods. ML algorithms are superior to conventional statistical models because they can analyze larger datasets and interpret nonlinear relationships in the given data. In patients with cervical spondylotic myelopathy, Khan et al. [87] used polynomial SVM learning to identify patients at risk of functional deterioration following surgery. The study included 757 patients, and the reported accuracy of detection was approximately 74.3%. McGrit et al. [88] examined data from 750 to 1,200 patients undergoing low back surgery and used regression analysis to predict the Oswestry Disability Index 1 year after surgery with an accuracy of up to 84%. Kim et al. [89] observed the incidence of postoperative C5 palsy in patients with OPLL and reported superior efficacy of ML algorithms with logistic regression models in the prediction of C5 palsy. Several similar studies using ML algorithms have reported outcome prediction following cervical and lumbar spine surgeries [90-92]. Hopkins et al. [93] performed a retrospective study of 4,046 patients undergoing posterior spinal fusion surgeries and identified patients at risk of developing surgical site infection using AI protocols. They reported positive and negative predictive values of 92.56% and 98.45%, respectively [93]. Hemiplegia/paraplegia, multilevel fusion, congestive cardiac failure, chronic pulmonary failure, and cerebrovascular disease were the risk factors with the highest significance in their study.

The spine is the most common site of skeletal metastasis, and approximately 70% of patients with malignancy could develop spinal metastasis [94]. Postoperative outcomes and overall survival rates in these patients have improved over the years. Karhade et al. [95] analyzed 1,790 patients with spinal metastasis and deployed Bayesian algorithm (ML) to identify 30-day mortality rates following spinal metastasis surgery. An open-access web application was also developed to identify these high-risk patients using ML algorithms. The authors concluded that as the volume of data in oncology increases, the creation of learning models and use of these systems as accessible tools may significantly enhance prognosis and appropriate management. A similar study included 1,053 patients with spinal epidural abscesses and showed promising results on the internal validation of ML algorithms to predict in-hospital and 90-day postdischarge mortality in these patients [96]. AI has thus emerged as a decision support tool, enabling surgeons' clinical decision-making process to be augmented by their predictive power. In addition to these clinical utilities, computer vision-based algorithms record the rehabilitation and functional assessment of patients with spinal cord injury. Likitlersuang et al. [97] designed a tool using an egocentric camera system to detect the functional interactions of the hand with objects during activities of daily living in patients with cervical spinal cord injury during rehabilitation. This device can directly collect quantitative information on hand functions in home and community settings.

AI in evidence-based spine research

With the introduction of AI systems, the term "smart gait" is becoming popular, where an integrated human gait data analysis such as human activity recognition, gait phase detection, gait event prediction, fall detection, recognition of a person's age and sex, and abnormal gait detection using AI tools can be performed. One of the important clinical signs in patients with radiculopathy caused by lumbar degenerative conditions is the listing of their trunk. This could alter the weight-bearing areas of the feet and cause variations in the gait pattern. Hayashi et al. [98] used SVM algorithms to analyze gait alteration in patients with L4 and L5 radiculopathy caused by lumbar canal stenosis and reported an accuracy of 80.4%. Similar published studies in the AI literature have focused on the identification of loads and stress patterns in various ligaments and joints of the foot, ankle, and knee, ensuring their use in orthopedic disorders such as adult-acquired flatfoot and osteoarthritis.

Adult spinal deformity is a complex pathology with heterogeneous clinical presentation and management options. Ames et al. [99] applied hierarchical clustering using AI to propose a classification model that would guide surgeons in deciding the appropriate surgical treatment. They are mainly useful in identifying patients at low risk and those likely to improve with surgical procedures. Regarding spinal fixation in these patients, pedicle screw instrumentation is preferred for deformity correction to regain sagittal and coronal balance. Several finite-element studies on the biomechanical properties and pullout strength of pedicle screws have been performed. However, these studies could not be individualized to patient-specific factors such as osteoporosis and sarcopenia, which are more prevalent in this population. Practically, the surgeon appraises the screw hold only by subjectively assessing the insertional torque of the screws. An experimental model to assess the pullout strength of pedicle screws using ML was developed by Khatri et al. [100], and they studied various parameters such as pedicle screw insertion angle, depth, density, and reinsertion. They observed that the model would also have a good clinical application with the inclusion of variables from the patient database, such as age, bone mineral density, and levels of activity. In addition, the authors suggested that failure mechanisms such as toggling and cyclical loading of pedicle screws can be investigated by incorporating the AI database.

Ethical concerns and future perspectives

Although the effects and contributions of AI and ML could be largely rewarding, the validity of the input data must be thoroughly investigated along with the integration of unstructured, scattered data to avoid erroneous predictions. External validation studies are needed to confirm the clinical efficacy in patients [8]. Selection biases could be a problem with these algorithms because the population data used for machine training may not necessarily be representative of the overall patient population. Another medicolegal consideration is the security and privacy of the patient data necessary for training these tools because it could result in breaches in the confidentiality of patient databases and cyber theft. Thus, data collection must be regulated in AI depository software to avoid privacy disclosure. During the early phase of their use, the need for data scientists to interpret health data could be one of the barriers to the widespread use of AI.

Many institutions, medical device companies, and pharmaceuticals have received significant incentives and funding to promote newer innovations such as AI and ML. These AI algorithms must not be programed to recommend specific pathways to increase the prioritization of designers and their funding companies. An ethical and regulatory framework must be developed for these algorithms so that AI can operate within well-defined norms.

In a recent systematic review, Liawrungrueang et al. [101] observed that AI and its integration with augmented reality (AR) and virtual reality (VR) appears promising for improving overall surgical safety. They also stated that VR surgical simulators create a secure environment for targeted surgical scenarios and foster self-guided learning. These extensive datasets can be processed by AI programs and aid in a deeper understanding of specific performance metrics during simulated operative tasks. In minimally invasive spine procedures, combining AR in the surgical workflow would be a major improvement because it would provide a 3D visualization of the anatomical structures. Considering all the effects of AI, in the coming years, it will serve as an invaluable additive tool in the surgical armamentarium; however, it could never replace the vast clinical knowledge and skills of surgeons.

Conclusions

AI and ML are emerging as promising tools in various aspects of healthcare. In spine surgery, they would serve as a valuable augmentation for clinicians to support their decision-making and make a more accurate calibration of the treatment plan. Thus, the future of AI is quite imminent, and these models could transform the practice of reactive medicine into an era of predictive, preventive, and personalized patient care.

Conflict of Interest

No potential conflict of interest relevant to this article was reported.

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