A narrative review of machine learning as promising revolution in clinical practice of scoliosis

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Abstract: Machine learning (ML), as an advanced domain of artificial intelligence (AI), is progressively changing our view of the world. By implementing its algorithms, our ability to detect previously undiscoverable patterns in data has the potential to revolutionize predictive analytics. Scoliosis, as a relatively specialized branch in the spine field, mainly covers the pediatric, adult and the elderly populations, and its diagnosis and treatment remain difficult. With recent efforts and interdisciplinary cooperation, ML has been widely applied to investigate issues related to scoliosis, and surprisingly augment a surgeon's ability in clinical practice related to scoliosis. Meanwhile, ML models penetrate in every stage of the clinical practice procedure of scoliosis. In this review, we first present a brief description of the application of ML in the clinical practice procedures regarding scoliosis, including screening, diagnosis and classification, surgical decision making, intraoperative manipulation, complication prediction, prognosis prediction and rehabilitation. Meanwhile, the ML models and specific applications adopted are presented. Additionally, current limitations and future directions are briefly discussed regarding its use in the field of scoliosis. We believe that the implementation of ML is a promising revolution to assist surgeons in all aspects of clinical practice related to scoliosis in the near future.

Keywords: Scoliosis; machine learning (ML); revolution; clinical practice

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Introduction

The past few decades have seen a massive increase in the use of artificial intelligence (AI). Machine learning (ML) is an advanced branch of AI that allows computer algorithms to learn patterns by studying data directly without being explicitly programmed. ML is similar to the human neural network that can learn, make decisions, communicate, and adapt to changing circumstances (1). Generally, ML is categorized into three primary methods: supervised, unsupervised, and reinforcement learning (2). Also, ML lends itself well to image processing due to its extremely high classification performance, and there have been a few studies regarding its applications to medical imaging (3). By implementing such methods, it is possible to revolutionize predictive analytics for previously undiscoverable patterns by leveraging existing big data, and it might have widespread implications for medical research.

Compared to other industries, healthcare is relatively slow in adopting AI (4). The incredible complexity of healthcare delivery is strangely what makes it a very fertile ground for the application of AI (5). However, technology is constantly changing throughout clinical practice, including how doctors interact with patients, diseases and their implements, the approach of information delivery, how the resultant interpretation is used to aid physicians, and postoperative evaluation and rehabilitation (6). The first attempts to introduce AI in spine surgery dated back to the advert of general-purpose computers during the Second World War and became available for nonmilitary use in the 1950s, which have been providing new insights into previous untapped and rapidly growing sources of data for reasoning and deciding. Nowadays, ML is entering the realm of medicine at an increasing pace and increasingly being used to investigate spine-related issues, especially in radiological imaging. For example, Jamaludin *et al.* (7,8) ever proposed a ML based system (Oxford SpineNet software system) for automatically analyzing spinal T2 MRI scans acquired from a DICOM (Digital Imaging and Communications in Medicine) file to evaluate Pffirrmann grades, modic changes, and spinal stenosis, and found that the system can be beneficial in aiding clinical diagnoses in terms of objectivity of gradings and the speed of analysis. In addition, ML is also applied in the outcome prediction of treatments (9). Arvind *et al.* (10) included 20,879 patients following anterior cervical discectomy and fusion and found that ANN have the greatest sensitivity in predicting mortality and postoperative complications. Similarly, Kim *et al.* (11) also reported the superiority of ML in identifying risk factors of developing complications following posterior lumbar spine fusion. Other applications of ML in spine surgery included diagnosis and assessment of spinal disease progression, decision-making in the treatment of spine degenerative diseases, and preoperative planning and intraoperative assistance (12).

Scoliosis, as a major composition of complex three-dimensional spine deformity, mainly covers the pediatric, adult and the elderly populations, and its diagnosis and treatment remain difficult. For decades, surgeons in this field relied on the established literature, extensive training, and clinical judgment to counsel patients regarding the risks and benefits of surgery; often, the most accurate information was based on their overall personal clinical experience and lacked patient-specific characteristics. With recent efforts and interdisciplinary cooperation, ML has been widely applied to investigate issues related to scoliosis (2,13). In this realm of enhanced technology and digital innovation, we are witnesses to this revolution and transformation. Surgeons in this field have been quickly adapting and refining these new technologies and integrated them into their clinical practice. The current trends in scoliosis are about digitization, ML, and smart robotics (14). ML models can meaningfully augment a surgeon's ability in clinical practice related to scoliosis. As a result, there has been more considerable interest in the literature and academic forums about the utilization of ML in various branches in this field.

In this article, we did a wide search in the PubMed and Embase databases, and the searching strategy applied was as follows: Machine Learning [All Fields] AND ("Scoliosis" [MeSH Terms] OR "Spine Deformity" [All Fields]). Based on the cited references, we enlarged the search range and adopted the useful publications. By means of this narrative literature review, we aim to raise awareness of the current achievements and potential applications of ML in the field of scoliosis. It is vitally important to have the ability to establish an accurate clinical practice procedure, including screening, diagnosis and classification, surgical decision making, intraoperative manipulation, complication prediction, prognosis prediction and rehabilitation (*Figure 1*), in selecting the most appropriate management strategy for disorders in this field, as shown in *Table 1*. Therefore, this paper firstly presents ML and its recent advances, which might have a dramatical impact on clinical practice procedures in treating scoliosis. We present the following article in accordance with the Narrative Review reporting checklist (available at http://dx.doi.org/10.21037/atm-20-5495).

Screening, diagnosis, and classification

Currently, imaging identification has become a tremendous field of ML. Given the characteristics of a regular sequence of the normal spine and the irregularity of scoliosis, ML has superiority in identifying this disorder. To efficiently screen and diagnose a patient with scoliosis, ML has been transformative.

Screening may detect scoliosis earlier than it would be clinically detected. With early detection, most cases can be controlled with the lower costs and better efficacy. In addition, accurate diagnosis with ML can help surgeons avoid misjudgment. Early in 2000, Jaremko *et al.* (15) was the first to use neural networks to correlate spine and rib deformities in scoliosis. The investigators compared artificial neural networks (ANNs) and linear regression to predict rib rotation, with the results that ANNs averaged 60% correct predictions compared to 34% for linear regression analysis. These data lend credence to using ANNs in future work on the prediction of scoliotic spinal deformities from

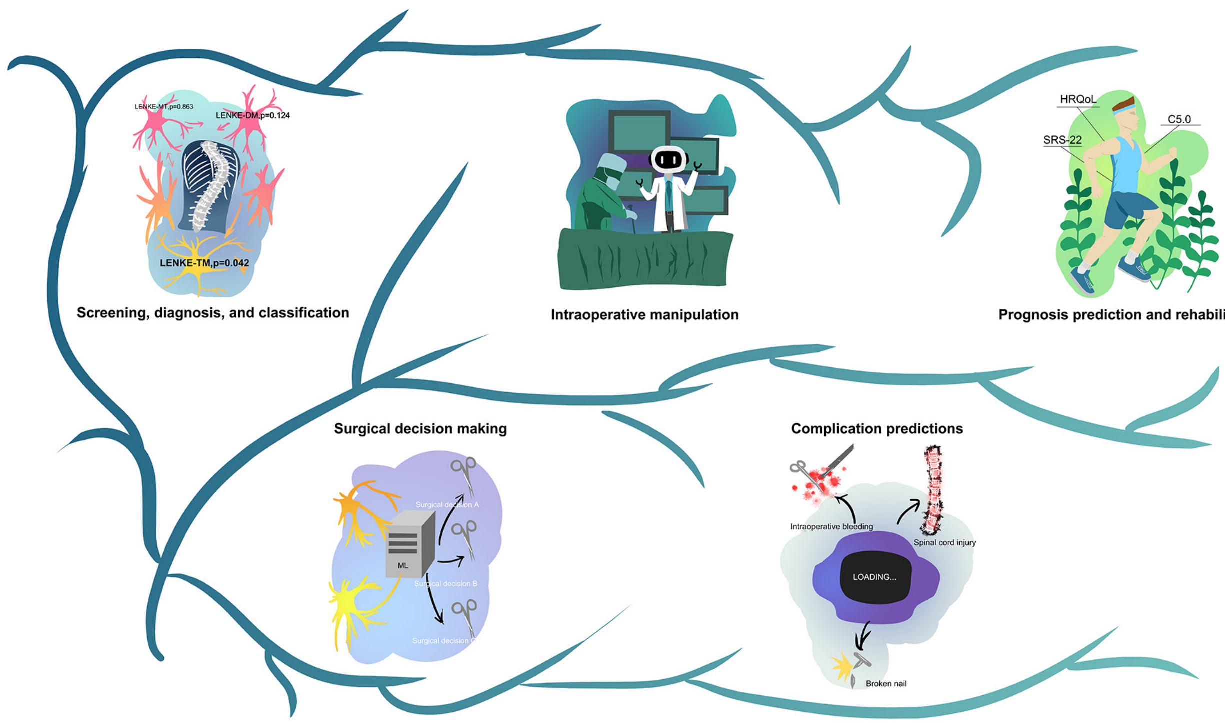

Figure 1 The demonstration of the application of ML in the clinical practice of scoliosis.

Table 1 The application of machine learning in the clinical practice of scoliosis

Study	Year	Number of data	Algorithms applied	Objectives	Outcome presentation
Screening, diagnosis and classification					
Jaremko (15)	2000	57 curves	ANN, linear regression	Predicting rib deformity	ANN showed good sensitivity and PPV
Jaremko (16)	2001	65 radiograph-pairs	ANN	Estimating spinal deformity from torso surface cross sections	Distinguished a Cobb angle greater than 30° with excellent sensitivity and specificity
Ramirez (17)	2006	111 patients	SVM	Assessing the severity of IS from surface topography	Satisfactory accuracy in testing
Lin (18)	2008	37 spinal deformity patterns	A multilayer feed-forward, back-propagation ANN	Identifying the King classification patterns of the scoliosis	Excellent identification rate for one or two hidden layers
Duong (19)	2010	200 radiographs	SVM	Automatically detecting scoliotic curves	Statistically similar to the manually identified curve
Adankon (20)	2012	165 AIS patients	Least-squares SVM	To determine scoliosis curve types using noninvasive surface acquisition	Excellent overall accuracy of the system
Menon (21)	2014	62 cases of AIS	–	Retrieving images of similar cases of AIS	–

Table 1 (*continued*)

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Study	Year	Number of data	Algorithms applied	Objectives	Outcome presentation
Birtane (22)	2014	25 scoliosis models and 10 X-rays	Two steps: (I) rule-based imaging processing and enhancing technologies; (II) a rule-based fuzzy classifier	Classifying the spine patterns using the King-Moe classification	Excellent success rate on scoliosis models and good success rate on real scoliosis X-rays
Thong (23)	2016	663 patients	A stacked autoencoder consisting of a specific ANN architecture; k-means++ clustering algorithm	Performing a 3D morphological analysis of spine	The model can simplify the complex nature of 3D spine models as well as preserve the intrinsic properties
Bertoncelli (24)	2018	120 patients	A predictive model based on a logistic regression algorithm	Validating the performance of a clinical prediction model	Good average accuracy, sensitivity, and specificity
García-Cano (25)	2018	150 AIS patients	Random forests	Predicting spinal curve progression	The estimated shape differs from the real curvature by Cobb angles in the proximal thoracic, main thoracic, and thoraco-lumbar/lumbar sections
García-Cano (26)	2018	962 3D spine models	Dynamic ensemble selection	Assessing curve types	A mean accuracy of 0.7766 and a mean log loss of 0.5623
Greer (27)	2018	10,000 images	A convolutional network and a second fully connected network	Diagnosing scoliosis using a self-contained ultrasound device	The mean error is 2.0°, the standard deviation is 3.7°, and the 95th percentile error is 5.8°
Wu (28)	2018	526 X-ray images	A novel multi-view correlation network	Automatically quantitative estimating spinal curvature	4.04° CMAE in anteroposterior (AP) Cobb angle and 4.07° CMAE in lateral (LAT) Cobb angle estimation
Galbusera (29)	2019	493 3D reconstructions	A fully CNN featuring an additional differentiable spatial to numerical transform (DSNT) layer	Automatically determining the spine shape and anatomical parameters	The standard errors of the estimated parameters ranged from 2.7° (for the pelvic tilt) to 11.5° (for the L1–L5 lordosis)
Yang (30)	2019	3,240 patients	A deep learning algorithm combined with Faster-RCNN and Resnet	Automatically screening scoliosis using unclothed back images	PPVs of 85.2% for a curve ≥10° and a specificity of 90.0% when identifying scoliosis and cases with a curve ≥20°
Watanabe (31)	2019	1,996 pairs of moiré images and standing whole-spine radiographs	CNN	Estimating spinal alignment from moiré images	The MAE per person between the Cobb angle measured by doctors and the estimated Cobb angle was 3.42°. The MAE was 4.38° in normal spines, 3.13° in spines with a slight deformity, and 2.74° in spines with a mild to severe deformity. The MAE of the angle of vertebral rotation was 2.9°±1.4° and was smaller when the deformity was milder
Wang (32)	2019	526 X-rays	Multiview extrapolation net	Accurately and automatically estimating Cobb angle	7.81 and 6.26 CMAE in AP and LAT angle estimation
Horng (33)	2019	35 images	CNN	Proposing an automatic system to measure spine curvature	Excellent results of ICC and Pearson correlation coefficients

Table 1 (*continued*)

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Study	Year	Number of data	Algorithms applied	Objectives	Outcome presentation
Pan (34)	2019	248 chest X-rays	Mask R-CNN	Automatically measuring the Cobb angle	A high level of sensitivity and a relatively low level of specificity for diagnosing scoliosis
Jamaludin (35)	2020	12,000 manually annotated images	Machine learning techniques of SpineNet software	Automating the identification of spinal curvature	The final automated model had an excellent sensitivity and specificity
Surgical decision making					
Mezghani (36)	2012	1,776 S cases	A topologically ordered self-organizing Kohonen network	Produce two spatially matched maps; determine where the Lenke classes correlate with the fused spine regions	Excellent overall agreement
Phan (37)	2013	1,776 patients	Kohonen self-organizing maps (SOM)	Reliably classifying AIS cases; analyzing surgeon's treatment patter	The topographic error for the SOM generated was small
Lafage (38)	2018	–	Machine learning	Optimizing surgical planning and predicting postoperative alignment	The use of powerful computer-assisted tools can change the traditional way of selecting treatment pathways
Ames (39)	2019	570 patients	Unsupervised machine-based clustering	Optimizing overall quality, value, and safety for ASD surgery	The intersection of patient-based and surgery-based clusters yielded 12 subgroups, with less major complication rates and good 2-year normalized improvement
Pasha (40)	2020	71 consecutive Lenke 1 B and C AIS patients	A decision tree	Defining criteria for optimal lumbar curve correction	The averages of the optimal versus suboptimal range of SLCC% in the cohort were 72%versus 39%
Intraoperative manipulation					
Benameur (41)	2005	30 pairs of radiographic images	A hierarchical statistical modeling	Present a new and accurate 3D reconstruction technique for the scoliotic spine	The mean error is 1.46–1.47 mm for lumbar vertebra and 1.30–1.32 mm for thoracic vertebra
Mirzaalian (42)	2013	22 vertebrae from 7 patients	Statistical shape modeling and machine learning	Realizing fast and robust 3D Vertebra Segmentation	The results indicate a lower symmetric point-to-mesh surface error
Amaritsakul (43)	2013	35 screw designs	ANN and genetic algorithm	Optimize design of spinal pedicle screws	The optimal design was inferior to commercial screws
Forestier (44)	2017	–	–	Realizing automatic matching of surgeries to predict surgeons' next actions	This method outperformed the state-of-the-art method
Hetherington (45)	2017	20 participants	Deep CNN	Realizing automatic spine level identification system	88% 20-fold cross-validation accuracy
Esfandiari (46)	2018	40 clinical X-rays	CNN	Realizing automatic segmentation of pedicle screws	The screw shafts with good accuracy on synthetic X-rays and clinically realistic X-rays

Table 1 (*continued*)

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Study	Year	Number of data	Algorithms applied	Objectives	Outcome presentation
Zareie (47)	2018	18 3D vertebrae CT images of thoracic and lumbar spine	Multilayer perceptron neural network; pulse coupled neural network and pulse coupled neural networks	Realizing automatic segmentation of vertebrae in 3D CT images	Similar and promising performance in both systems
Ebrahmi (48)	2019	149 healthy and AIS subjects	A quasi-automated pedicle localization method based on image analysis, machine learning and fast manual identification of a few landmarks	Detecting pedicle and estimating vertebral rotation	Pedicles centers were localized with a better precision of compared with manual identification
Huo (49)	2020	400 individual vertebral models	A modified PointNet model (CNN)	Automatically recognizing the vertebral pedicle in individual vertebral models and drawing pedicle contours	The final results can be used to simulate the operation of pedicle screw implantation and to provide a reference
Complication predictions					
Scheer (50)	2016	510 patients	An ensemble of decision trees using the C5.0 algorithm with 5 different bootstrapped models	To create a preoperative predictive model for proximal junction failure (PJF)	The overall model accuracy indicated a good model fit
Scheer (51)	2017	557 ADS patients	An ensemble of decision trees utilizing the C5.0 algorithm with 5 different bootstrapped models	To create a preoperative predictive model for major complications	The overall model accuracy indicated a very good model fit
Kim (52)	2018	4,073 ADS patients	ANN	To predict surgical complications in patients	The ANN outperformed logistic regression in predicting cardiac complication, wound complication, and mortality
Yagi (53)	2018	145 surgically treated ASD patients	Decision-making trees using the C5.0 algorithm with 10 different bootstrapped models	To fine tune the predictive model for PJF	The predictive model indicated excellent fit
Pellisé (54)	2019	1,612 ASD patients	Random survival forest algorithm	To develop and validate a prognostic tool for the time-to-event risk of major complications (MCs), hospital readmission (RA), and unplanned reoperation (RO)	Kaplan-Meier estimates showed that longer duration after operation frequently accompanied with high risk of MC
Yagi (55)	2018	195 surgically treated ASD patients	An ensemble of decision trees utilizing the C5.0 algorithm with 5 different bootstrapped models	To create a predictive model for complications	92% accurate with an AUROC curve of 0.963 and 84% accuracy in the external validation

Table 1 (*continued*)

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Study	Year	Number of data	Algorithms applied	Objectives	Outcome presentation
Hopkins (56)	2020	4,046 posterior spinal fusions	Deep neural network (DNN) classification model	To prex surgical site infection	The mean AUC was 0.775 (95% CI: 0.767–0.782) with a median AUC of 0.787. The PPV over all predictions was 92.56% with a negative predictive value (NPV) of 98.45%
Prognosis prediction and rehabilitation					
Chalmers (57)	2015	28 braced patients	Conditional fuzzy C-means clustering	To provide meaningful treatment for AIS patients	Sensitivities for the panel and model were excellent
Sim (58)	2015	10 healthy people and 10 AIS patients	Wavelet neural network	To predict complete GRF and GRM during gait with insole plantar pressure information	The performance of the GRF and GRM prediction models were better than that of previous prediction models
Oh (59)	2017	234 patients with ASD	An ensemble of 5 different bootstrapped decision trees was constructed using the C5.0 algorithm	To assist in preoperative patient selection	A successful model was constructed to predict which patients would reach ODI MCID
Scheer (60)	2018	198 ADS patients	Decision trees were constructed using the C5.0 algorithm with five different bootstrapped models.	To create a preoperative predictive model for reaching the ODI MCID for ASD patients	Overall model accuracy was 86.0%
Ames (61)	2019	561 ADS patients	Elastic net, gradient boosting machines, extreme gradient boosting tree, extreme gradient boosting linear, random forest and elastic net regularized generalized linear models	To create preoperative predictive models for responses to individual SRS-22R questions at 1 and 2 years	The AUROC ranged from 56.5 to 86.9%
Ames (62)	2019	570 ADS patients	Partitions, elastic net, gradient boosting machines, extreme gradient boosting tree, extreme gradient boosting linear, random forest, and generalized linear modeling	To predict the likelihood of reaching MCID in patient-reported outcomes after ASD surgery	Models with the lowest MAE were selected; R^2 values ranged from 20% to 45% and MAE ranged from 8% to 15% depending upon the predicted outcome

ANN, artificial neural network; AIS, adolescent idiopathic scoliosis; SVM, support vector machine; PPV, positive predictive value; CNN, convolutional neural network; CMCE, circular mean absolute error; ASD, adult spinal deformity; GRF, ground reaction forces; GRM, ground reaction moments; ODI, Oswestry Disability Index; MCID, minimal clinically important difference.

the torso surface. Regarding neuromuscular scoliosis, Bertoncelli *et al.* (24) applied a predictive model based on a logistic regression (LR) algorithm to predict the probability of scoliosis onset. The predictive accuracy, sensitivity, and specificity of the model were approximately 74% in full accordance with recent studies applying ML models in clinical fields.

A noninvasive method was gradually developed to assess scoliosis. Jaremko *et al.* (16) adopted ANNs to quantify torso surface asymmetry, and this method estimated the maximal Cobb angle within 6° in 63% of the test data set and was able to distinguish a Cobb angle greater than 30° with a sensitivity of 100% and specificity of 75%. However, it is worth mentioning that this research had a small data set with only 65 scan-radiograph pairs, which is not very persuasive. An increasing number of harmless screening methods have been developed, and a support vector machine (SVM) classifier has been used to assess the severity of idiopathic scoliosis based on surface topographic images of human backs by Ramirez *et al.* (17). The results of testing on the dataset showed that the system can achieve 69–85% accuracy in testing. Yang *et al.* (30) used unclothed back images with a combination algorithm of Faster-RCNN and Resnet to screen adolescent idiopathic scoliosis (AIS), and this research included images from 3,240 patients. Watanabe *et al.* (31) created a scoliosis screening system that estimated spinal alignment, the Cobb angle, and vertebral rotation from moiré images based on a convolutional neural network (CNN) to estimate the positions of 12 thoracic and 5 lumbar vertebrae, 17 spinous processes, and the vertebral rotation angle of each vertebra. Using self-contained ultrasound as another detection method for scoliosis, Greer *et al.* (27) estimated the Cobb angle relative to a vertebrae using a neural network analysis, which was based on a convolutional network and a second fully connected network.

It is important to develop an automatic procedure since measuring the Cobb angle can be time consuming and unreliable. Duong *et al.* (19) adopted SVM to quantify curve severity with 100 posteroanterior radiographs, and the results were statistically similar ($P<0.05$) in 93% of cases to the manually identified curve. Wu *et al.* (28) proposed a novel multi-view correlation network (MVC-Net) architecture that provided a fully automated end-to-end framework for spinal curvature estimation in multi-view (both anteroposterior (AP) and lateral (LAT)) X-rays. The results indicated that the MVC-Net's capability of estimating Cobb angles from multi-view X-rays was robust and accurate. Wang *et al.* (32) also proposed a multi-view extrapolation net (MVE-Net) that provided accurate automated scoliosis estimation from both AP and LAT X-rays. CNN is another suitable ML algorithm for Cobb angle measurement. Galbusera *et al.* (29) extracted the location of 78 landmarks from three-dimensional reconstructions of 493 spines of patients suffering from various disorders and trained a fully CNN featuring an additional differentiable spatial to numerical transform (DSNT) layer to predict the location of each landmark. This model automatically determined the shape of the spine in biplanar radiographs and calculated the value of anatomical and posture parameters across a wide range of clinical conditions with robust performance. Horng *et al.* (33) ever created a CNN system that included three main parts: isolation of the spine, vertebra segmentation, and Cobb angle measurement. Pan *et al.* (34) proposed two Mask R-CNN models to automatically measure the Cobb angle and diagnose scoliosis on chest X-ray. Jamaludin *et al.* (35) automated the identification of spinal curvature from total body dual-energy X-ray absorptiometry (DXA) scans using ML techniques, and the final automated model had a sensitivity of 86.5%, specificity of 96.9%, and an area under the curve (AUC) of 0.80 (95% CI: 0.74–0.87). To dynamically monitor spinal curve progression in AIS, García-Cano *et al.* (25) proposed a novel approach based on a statistical generative model using random forest regression to predict the shape variation in the spinal curve from the first visit. The estimated shape differed from the real curvature by Cobb angles of 1.83°, 5.18°, and 4.79° in the proximal thoracic, main thoracic, and thoracolumbar/lumbar sections, respectively.

The primary goal of surgical management of scoliosis is to achieve solid fusion with a well-balanced spine. Insufficient understanding of curve morphology and subsequent improper selection of fusion levels may result in suboptimal outcomes (62). Classification has provided guidance in the treatment of spine deformities. However, though AIS and adult degenerative scoliosis (ADS) are the most common spinal deformities, there can be of great variety in their classification. In this context, identification of AIS classification has been an important topic in the orthopedic community, while ADS classification can be more complex and irregular. Lin *et al.* (18) implemented a multilayer feed-forward, back-propagation (MLFF/BP) ANN to test the King classification of scoliosis spinal deformity. The identification rate was 83% for two hidden layers and 75% for one hidden layer. Other noninvasive classification methods are also being explored. Adankon *et al.* (20) divided the 3D image of the surface of the trunk into patches and local geometric descriptors characterizing the back surface of 165 patients with different scoliosis curve types and built a multiclass classifier with least-squares support vector machines (LS-SVM). The overall accuracy of the system was 95%. For the correct classification rates per class, the results showed 96%, 84% and 97% for the thoracic, double major and lumbar/thoracolumbar curve types, respectively. To solve the problem of low interobserver and intraobserver reliability in AIS classification, García-Cano *et al.* (26) presented two new techniques to describe the spine, namely, leave-one out and fan leave-one-out for characterizing spine curve types, and provided assistance to clinicians in the form of information to classify borderline curvature types. Moreover, a fuzzy logic rule-based classifier was also implemented to classify the spine patterns using the King-Moe classification approach by Birtane *et al.* (22). As spine deformities are three-dimensional deformities, an increasing number of researchers have paid attention to its 3D classification. Thong *et al.* (23) adopted an unsupervised clustering method based on stacked autoencoders to simplify the complex nature of 3D spine models. It is noteworthy that any classification has its advantages and disadvantages, and therefore, it is hard to evaluate which is better. The world is moving into digital archiving, retrieval, and communication of high-resolution images. Menon *et al.* (21) proposed a newly developed content-based image retrieval (CBIR) software to retrieve images of similar cases of AIS from a database to help plan treatment without adhering to a classification scheme. Although this software did not elaborate a thorough algorithm and the sample size was quite small, this concept is extremely promising for future scoliosis classification.

Surgical decision making

Classification can truly aid in decision making and instrumentation region selection for surgeons. For example, the Lenke classification (63) provides guidelines for arthrodesis for 6 types and 42 subtypes of AIS patients using expert opinion/consensus and available scientific evidence for clinical decision making; the Scoliosis Research Society (SRS)-Schwab classification (64) and Lenke-Silva classification (65) provide surgical instructions from the perspective of morphology and management for ADS patients. To make this procedure more evidence-based, ML has potential.

Regarding AIS, Mezghani *et al.* (36) used a database of 1,776 surgically treated AIS cases and investigated a topologically ordered, self-organizing Kohonen network trained using Cobb angle measurements to determine the relationship between the Lenke classification and fusion region selection. The results showed that the recommended fusion region by ML model agreed with the Lenke classification with 88% overall agreement. Surgery planning could benefit from such map associations by comparing treatment outcomes from similar patients receiving different treatments. Phan *et al.* (37) used neural networks and Kohonen self-organizing maps (SOM) to classify AIS and conducted a retrospective analysis of AIS curve regions selected for fusion. An AIS SOM with high accuracy was successfully generated. Lenke classification principles were followed in 46% of the cases but in 82% of the nodes on the SOM. The SOM highlighted the tendency of surgeons to follow Lenke classification principles for similar curves on the SOM. To identify the range of optimal versus suboptimal rates of spontaneous lumbar Cobb correction (SLCC) and the factors predicting such outcomes in a cohort of Lenke 1 AIS patients, Pasha (40) adopted a decision tree to analyze 71 consecutive AIS patients with a fusion level to L1 and concluded that preoperative lumbar apical vertebrae translation, early postoperative T4–T12 thoracic kyphosis and thoracic apical vertebrae rotation can predict the optimal range of SLCC%.

As for adult spinal deformities, the principles regarding surgery can be different from AIS and other types of deformities. Health-related quality of life (HRQoL) can be tightly correlated with sagittal alignment. Ames *et al.* (39) included 570 ADS patients and adopted AI-based hierarchical clustering as a step toward a classification. The results showed that this model identified data patterns that may augment preoperative decision making through the construction of a 2-year risk–benefit grid. Additionally, pattern identification may facilitate treatment optimization by educating surgeons on which treatment patterns yield optimal improvement with the lowest risk. Lafage *et al.* (38) adopted ML and other types of advanced algorithms to improve surgical outcomes and alignment predictions for surgical planning and prediction of postoperative alignment. These tools, which were able to integrate several parameters and learn from experience, can change the traditional way of selecting treatment and counseling patients. However, the complete algorithm and sample quantity were not mentioned in the article.

Intraoperative manipulation

To better enhance the surgeon's intraoperative performance, a variety of applications combined with AI were put into routine use. Correct segmentation and vertebral reconstruction are crucial steps in the assessment and management of abnormalities, especially because vertebral rotation is difficult to simulate in spine deformities. Early in 2005, Benameur *et al.* (41) proposed a hierarchical statistical modeling approach for the unsupervised 3-D biplanar reconstruction of the scoliotic spine. Then, Mirzaalian *et al.* (42) applied a top-down fully automatic 3D vertebra segmentation algorithm using global shape-related and local appearance-related prior information, in which the latter was handled by a ML-based component. The results indicated a symmetric point-to-mesh surface error of 1.37±0.37 mm, which matched the current state-of-the-art methods. In 2018, Zareie *et al.* (66) compared a multilayer perceptron neural network (MLPNN) and a newly developed adaptive pulse coupled neural network (APCNN) in the automatic segmentation of vertebrae in 3D CT images and concluded that the performance of the presented APCNN-based algorithm was dominant.

Pedicle location and recognition play important roles in screw implantation for spine deformities. Huo *et al.* (48) proposed a method based on 400 individual vertebral models to automatically recognize the vertebral pedicle in individual vertebral models and draw pedicle contours. The procedure included three steps: first, the individual vertebral models were preprocessed to obtain their point clouds; then, a modified Point-Net model was used to segment the pedicle areas from the individual vertebral point clouds; afterwards, the segmentation results were used to automatically fit the cross-sections of pedicles and finally generate the pedicle contours as surgical references. For most scoliosis cases, vertebrae often have axial rotation, and this point should be taken into great consideration when inserting pedicle screws. Ebrahimi *et al.* (47) included a total of 149 healthy and AIS subjects and developed an automated pedicle detector based on image analysis, ML and fast manual identification of a few landmarks to calculate vertebrae axial rotation values in frontal radiographs with minimal user intervention and robust quasi-automated pedicle localization. Minimally invasive surgery is another promising strategy for spine deformities; therefore, accurate percutaneous spinal needle insertion procedures are necessary. Hetherington *et al.* (45) developed a real-time system based on deep CNN to classify transverse images of the lower spine, and this method might contribute to the development of a minimally invasive treatment for ADS. To satisfy the goal of verification, screw insertion was performed intraoperatively. Esfandiari *et al.* (46) found that the CNN framework was capable of segmenting screw shafts with 93% and 83% accuracy when tested on synthetic X-rays and on clinically realistic X-rays, respectively. To achieve the goal of multiobjective optimization design of spinal pedicle screws in the treatment of deformity corrections, Amaritsakul *et al.* (43) found that the hybrid of ANN and genetic algorithm (GA) was ideal with simultaneous high bending and pullout performances. Moreover, automatic matching of surgeries to predict the surgeons' next actions can be helpful for spine deformity surgeons. For this purpose, Forestier *et al.* (44) proposed an efficient algorithm to find the optimal partial alignment and a prediction system using maximum a posteriori probability estimation and filtering in lumbar disc herniation removal and anterior cervical discectomy. The results showed that this method outperformed the state-of-the-art methods by predicting the next task that the surgeon will perform with 95% accuracy. We believe this kind of mode can be extended to orthopedic surgeries for spine deformities in the near future.

Complication predictions

The definition of complication in this review was defined as adverse events that can significantly affect the patients' quality of life and frequently required clinical intervention during the perioperative period. The goal of surgical treatment for patients with scoliosis is undoubtedly to improve their HRQoL, and thus related complications should be carefully taken into consideration, especially in adult spinal deformity (ASD) patients. Any unexpected complication may cause miserable results, and it is of great importance to predict these problems before performing surgery. Normally, few complications are found in the AIS population, and nearly all the references regarding scoliosis and ML are about ADS. Pellisé *et al.* (53) aimed to assess the incidence of adverse events after ASD surgery and to develop and validate a prognostic tool for the time-to-event risk of major complications (MCs), hospital readmission (RA), and unplanned reoperation (RO). They created a random survival forest algorithm, and the results showed that surgical invasiveness, age, magnitude of deformity, and frailty were the strongest predictors of MCs. Individual cumulative risk estimates at 2 years ranged from 3.9% to 74.1% for MCs, from 3.17% to 44.2% for RAs, and from 2.67% to 51.9% for ROs. Scheer *et al.* (50) performed similar studies with ASD patients, and they constructed an ensemble of decision trees utilizing the C5.0 algorithm with 5 different bootstrapped models. With a sample of 557 ADS patients, the overall model accuracy was 87.6% correct, with an AUC of the receiver operating characteristic (AUROC) curve of 0.89 indicating a very good model fit. They reported that twenty variables were determined to be the top predictors. Kim *et al.* (51) created models using the American Society of Anesthesiologists classification (ASA class) as a benchmark for prediction of cardiac complications, wound complications, venous thromboembolism (VTE), and mortality in ASD patients. The results showed that the ANN outperformed LR in predicting cardiac complications, wound complications, and mortality (P<0.05). To analyze MC 2 years after corrective spine surgery for ASD, Yagi *et al.* (52) constructed decision-making tree models using spinal alignment, demographic data, and surgical invasiveness. The test samples showed that their predictive model was 92% accurate with an AUROC curve of 0.963 and 84% accuracy in the external validation. As patients with spine deformities often experience long and deep wounds, postoperative surgical site infection is a common complication. Hopkins *et al.* (55) trained a deep neural network classification model using 35 unique input variables in a retrospective cohort of 4,046 posterior spinal fusions. The overall rate of infection was 1.5%. The mean AUC, representing the accuracy of the model, across all 300 iterations was 0.775 (95% CI: 0.767–0.782) with a median AUC of 0.787. Although this research did not focus on scoliosis, the application of ML can be examined in future studies.

Regarding radiographic complications, especially proximal junctional kyphosis (PJK) and proximal junctional failure (PJF) in ASD patients, there were only two studies reported to date. Scheer *et al.* (49) constructed an ensemble of decision trees using the C5.0 algorithm with 5 different bootstrapped models in a cohort of 510 ASD patients, and the overall model accuracy was 86.3%, with an AUC of 0.89 indicating a good model fit. Their study listed the 7 strongest (importance ≥0.95) predictors: age, lowermost instrumented vertebra (LIV), preoperative sagittal vertical axis (SVA), uppermost instrumented vertebra (UIV) implant type, UIV, preoperative pelvic tilt (PT), and preoperative pelvic incidence and lumbar lordosis (PI-LL). In 2018, Yagi *et al.* (54) fine-tuned the predictive model for PJF with the construction of decision-making trees using the C5.0 algorithm with 10 different bootstrapped models and assessed performance with 145 surgically treated ASD patients. Their predictive model was 100% accurate in the testing samples with an AUC of 1.0, indicating excellent fit. The best predictors were (strongest to weakest): PT, bone mineral density (BMD), LIV level (pelvis), UIV level (lower thoracic), pedicle subtraction osteotomy (PSO), global alignment, body mass index (BMI), PI-LL, and age.

Prognosis prediction and rehabilitation

All surgeons crave for a better clinical efficacy for their patients; however, the prognosis across differing circumstances can be quite different. Therefore, prognosis prediction is necessary, and currently, different ML approaches are being explored according to their specific characteristics. Regarding functional indices, Scheer *et al.* (59) constructed decision trees using the C5.0 algorithm with five different bootstrapped models according to baseline demographic, radiographic, HRQoL, and surgical factors to predict patients meeting the Oswestry Disability Index (ODI) minimal clinically important difference (MCID) at the two-year postoperative follow-up. The overall model accuracy was 86.0%, with an AUC of 0.94, and the top 11 predictors for achieving the MCID were listed. Ames *et al.* (60) compared eight predictive algorithms using 75 variables of demographics, baseline patient-reported outcomes (PROs), and modifiable surgical parameters at four time horizons: preoperative or postoperative baseline to 1 year and preoperative or postoperative baseline to 2 years. They concluded that patients with worse preoperative baseline PROs tended to achieve clinically relevant improvements. This team also developed six different prediction algorithms for all the individual questions on the SRS-22R after ASD surgery directed toward individualized medicine, and the AUROC ranged from 56.5% to 86.9%, reflecting successful fits for most questions (61). Oh *et al.* (58) aimed to create a validated MCID model that had the potential to assist in patient selection, thereby improving outcomes. An ensemble of 5 different bootstrapped decision trees was constructed using the C5.0 algorithm with 85.5% accuracy and 0.96 AUC.

Regarding rehabilitation, Chalmers *et al.* (56) compared human experts' and a fuzzy model's predictions of outcomes of scoliosis bracing treatment. The model was constructed using conditional fuzzy C-means clustering to discover patterns in retrospective patient data and was capable of providing meaningful brace treatment recommendations. A wavelet neural network was adopted to predict complete ground reaction forces and moments during gait with insole plantar pressure information by Sim *et al.* (57), and the results might help improve the gait of AIS patients. In addition, a robotic spine exoskeleton (67) capable of controlling the position/orientation of specific cross-sections of the human torso while simultaneously measuring the forces/moments exerted on the body opened the possibility for the design of spine braces incorporating patient-specific torso stiffness characteristics and the potential for new interventions using the dynamic modulation of 3-D forces for scoliosis treatment. Additionally, robotic rehabilitation of the upper extremity after neurological injury (68) and trunk robot rehabilitation training with active stepping after trunk motor cortex injury (69) might be promising assistant rehabilitation methods in the near future.

Current limitations and future directions

The implementation of ML technologies for scoliosis, especially regarding tools with a direct clinical impact, is undoubtedly contributing to a paradigm shift. However, with the advent of new techniques, the current limitations and ethical problems should be reasonably considered. A systematic review in neurosurgical literature concluded that in spite of great potential of ML models in augmenting the decision-making capacity of clinicians in neurosurgical applications, significant hurdles remain associated with creating, validating, and deploying ML models in the clinical setting (1). Perhaps the most barrier regarding ML adoption is the lack of robust frameworks used to assess the performance and development of the related algorithms. Furthermore, the mechanisms driving the algorithms is sometimes complicated and even unpractical. In fact, there is an absence of clear gold criteria for ML models in addressing clinical problems. Regarding aspects of disease screening, diagnosis and classification, ML still shows the phenomena of misdiagnosis and missed diagnosis, and its accuracy is not 100% effective. Although there are many types and theories as support, many details remain to be optimized for more thorough and further simulation and planning. In addition, although ML is much more improved than simple mathematical statistics, the basic principle appears as a black box to an external user, and its predictions largely appear to be determined by an obscure logic that cannot be understood or interpreted by a human observer (70,71). Secondly, it is relatively difficult to collect high-volume patients' date for a single-center institution due to privacy considerations or across institutions. The deployment of such powerful technologies in the area of scoliosis is still in its infancy, and scoliosis is a relatively narrow branch of the spine field; the available number of samples is not as sufficient as other subjects. Thirdly, another important preconception regarding the role of ML models in clinical spine realm is that the status of clinicians could be shaken, a so-called term 'human-vs-machine' (72). In clinical practice, although ML could give high analysis accuracy in clinical guidance, the clinicians still must pay attention to the implications of this analysis (73). Researchers apply a variety of algorithms to develop applications, and the annotation and collection of the original data should be rigorous. Before extension to other surgeons, the application should require more comprehensive testing and verification with respect to other technologies. When applied in the real world, the surgeons' role in the final decision should still be emphasized (74). Last but not least, ethical problems should never be neglected with ML in the scoliosis field. Data privacy and security remain a problem due to the massive amount of clinical and imaging data required, thus issues about data collection, transmission and storage, as well as informed consent are involved (2). Data anonymization is commonly advocated; nevertheless, patients retain rights to their anonymized data, which are subjected to strict regulations about storage, transmission and use, especially when data are used in a for-profit environment (75).

Consequently, conducting a high-quality study may be restricted. Also, the ability to evaluate the study design such as power analysis can be limited. Therefore, it is imperative to reach a consensus regarding the optimal method standardization of ML in clinical practice, and a high-quality study taking human-and -machine approach may reveal how the clinicians can benefit from ML models. The following suggestion recommendations should be considered by clinicians when ML is applied in scoliosis. Firstly, a multidisciplinary team containing spine clinicians, engineers, statistical experts, and data scientists should be created to evaluate the ML tools, which could compensate to the knowledge limitations for any single team. Secondly, there was considerable heterogeneity in the modeling methods used, including the inclusion criteria, input and output variables used, and so on. The comparison of different neural network algorithms could assist in selecting the best model with the best performance. Additionally, the advantages and disadvantages of different algorithms for each spinal disorder should also be considered (76). Therefore, future study should focus on the validation of ML models on heterogeneous test sets prior to deployment and the regulation of ML performance after deployment in clinical practice. Thirdly, concept shifting from human *vs.* machine to human-and-machine may be essential to over these barriers. Take an example, there were four studies concluded that ML combining with clinical decision making is superior to ML models or clinical decision making alone (72,76-78). Using the experience of clinicians as a pre-requirement, the application of ML in spine deformity, such as scoliosis, will be more promising in increasing the accessibility of clinical data.

Conclusions

Currently, ML in practice is still an art of weak AI. Although we presented its application in different clinical practice stages, there is still a lack of a complete cycle of the clinical procedure that can help surgeons make decisions from diagnosis to prognosis. The related applications of ML on etiology (79), gait analysis (57) and electronic medical records analysis (80) should also be continued. We believe that the implementation of sophisticated ML for scoliosis promises a revolution in how surgeons perform throughout all aspects of the clinical practice related to scoliosis (14). More effective and reliable predictive models for new ways of collecting, accessing, sharing, storing, analyzing and presenting the data need further exploration.

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Footnote

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