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The Application of Artificial Intelligence in Spine Surgery: A Scoping Review

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None of the following authors or any immediate family member has received anything of value from or has stock or stock options held in a commercial company or institution related directly or indirectly to the subject of this article: Dr. Shi, Dr. Wang, and Dr. Shea.

Authorship contribution: Dr. Shi: acquisition and analysis of data, and drafting of manuscript; Dr. Wang: acquisition and analysis of data, and drafting of manuscript; Dr. Shea: study conception, drafting, and review of manuscript.

Dr. Shi and Dr. Wang contributed equally to this work.

JAAOS Glob Res Rev 2025;9: e24.00405

DOI: 10.5435/JAAOSGlobal-D-24-00405

ABSTRACT

Background: A comprehensive review on the application of artificial intelligence (AI) within spine surgery as a specialty remains lacking.

Methods: This scoping review was conducted upon PubMed and EMBASE databases according to Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines. Our analysis focused on publications from January 1, 2020, to March 31, 2024, with a specific focus on AI in the field of spine surgery. Review articles and articles predominantly concerning secondary validation of algorithms, medical physics, electronic devices, biomechanics, preclinical, and with a lack of clinical emphasis were excluded.

Results: One hundred five studies were included after our inclusion/exclusion criteria were applied. Most studies (n = 100) were conducted through supervised learning upon prelabeled data sets. Overall, 38 studies used conventional machine learning methods upon predefined features, whereas 67 used deep learning methods, predominantly for medical image analyses. Only 25.7% of studies (27/105) collected data from more than 1,000 patients for model development and validation. Data originated from only a single center in 72 studies. The most common application was prognostication (38/105), followed by diagnosis (35/105), medical image processing (29/105), and surgical assistance (3/105).

Conclusion: The application of AI within the domain of spine surgery has significant potential to advance patient-specific diagnosis, management, and surgical execution.

Introduction

Over the past decade, advances in artificial intelligence (AI) have evolved from being of academic interest to tools ready for use at the bedside. The capacity of AI to process a large amount of clinical data through sophisticated algorithms has surpassed the performance of seasoned physicians in selected contexts. Spine surgery is a medical discipline requiring not only astute clinical diagnosis but also meticulous surgical planning and execution. Given this breadth in the relevance of AI in spine surgery, it is invaluable that advances across the field—spanning both specific spine disorders and areas of application—may be summarized and critically appraised. This promises to provide insight into how research developments may be consolidated and refined toward benefitting patients. In this scoping review, we provide a comprehensive analysis of AI's role in spine surgery to date, with the objectives being to shed light on the current state of clinical integration and identify trajectories for future research and development.

Methods

Study Protocol

This scoping review was conducted in strict accordance with the principles of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses for Scoping Reviews.[1] The objective was to thoroughly chart the scope of literature concerning AI and spine surgery, with a particular focus on the integration of AI within clinical practice.

Inclusion and Exclusion Criteria

We employed a detailed search strategy, outlined in Supplementary Figure 1 (http://links.lww.com/JG9/A403), to identify articles listed upon PubMed and EMBASE databases and published between January 1, 2020, and March 31, 2024. Our search terms were selected to encompass AI-related technologies (including AI, machine learning [ML], deep learning [DL], and computer vision) alongside clinical and surgical aspects of spine surgery (medical image computing [MIC], assisted diagnosis, prognostication, surgical planning, and assistance). To ensure the incorporation of rigorously refereed articles of high quality, an additional inclusion criterion was the selection of articles published in journals ranked in the top 25% by Journal Citation Report (2023) impact factor rankings (JCR Q1) in the categories of "Clinical Medicine" and "Computer Science." We excluded abstracts, conference proceedings, reviews, commentaries, and editorial pieces. Studies without a clinically orientated focus were excluded. Article screening and selection was carried out independently by two experienced postgraduate researchers with a background in AI and clinical orthopaedics. Disagreements were resolved through reaching a consensus, ensuring that each selected article met our defined selection criterion.

Results

Search Results

As shown in Figure 1, our initial search yielded 2,959 results, of which 890 studies were published in JCR Q1 journals. An additional 785 publications were excluded following the evaluation of their title, abstract, and full text because they did not exhibit a predominant emphasis on the intersection between AI and spine surgery. A comprehensive analysis of these articles was conducted to concerning the application of AI in the field of spine surgery. Country of origin for the corresponding author among each included publication was analyzed. As shown in Figure 2, more than half of studies originated from China and the United States, corresponding to 43 (40.9%) and 25 (23.8%) articles, respectively. Overall, eight studies (7.6%) were from Japan and seven studies (6.7%) from Korea. Canada, Singapore, and Switzerland contributed three studies (2.9%) each, whereas the remaining 13 articles were published in other countries.

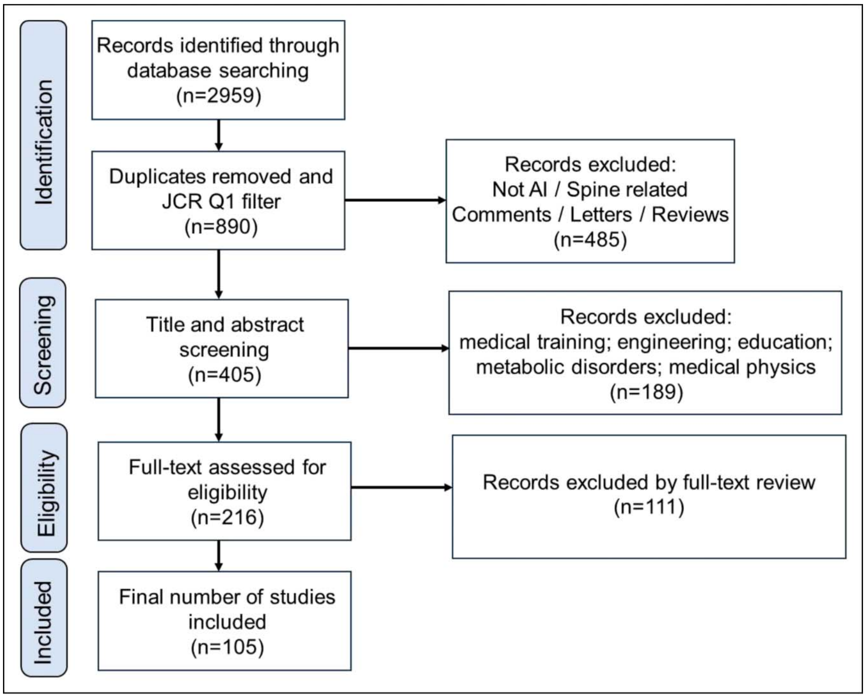
Clinical Data

Type of Data

Provision of clinical data is essential for DL. According to the type of input data, literature may be divided into being clinical parameters–based studies (n = 32), single-modality medical image–based studies (MRI [n = 25], CT [n = 13], radiograph [n = 22] and ultrasonography [n = 2]), sensor parameter–based studies (n = 4), and composite input-based studies (n = 7). Results are summarized in Figure 3.

As an example of clinical parameters, age, sex, disease duration, and preoperative Japanese Orthopedic Association score were integrated with ML methods to predict surgical outcomes in patients with degenerative cervical myelopathy (DCM).[2] Literature concerning MRI as input included two studies using quantified MRI features[3,4] and 23 studies using MRI images. The former approach relied on feature extraction software to quantify MRI features for ML input, such as for the classification of spinal tumors.[3] The latter directly approach employed DL to extract image features without prior feature engineering, such as for the automated detection of lumbar disk herniation (LDH).[5]

Figure 1



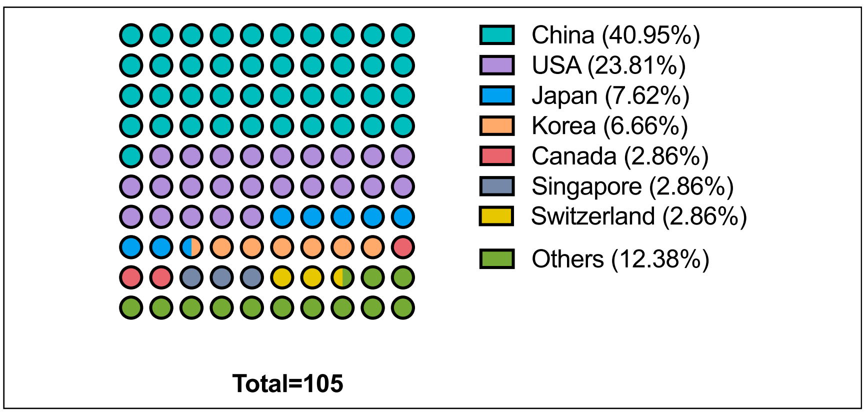
PRISMA flow diagram showing the scoping review process. PRISM = Preferred Reporting Items for Systematic Reviews and Meta-Analyses.

Overall, 21 studies used radiographic images directly as input, whereas one study used quantified radiograph morphological features.[6] Twelve studies considered CT images as input, and one study considered CT texture features.[7] Two studies on AI-based ultrasonography image segmentation considered scoliosis detection[8] and quantification of scoliosis-related measurements.[9]

Medical images may be combined with clinical parameters for AI modeling, with examples being radiographs,[10,11] MRI scans,[12,13] and CT scans in combination with clinical parameters.[7] Seven studies involved more than one data modality as input. Inputs of paired images were also reported from two studies for medical image synthesis, including the generation of lumbar spine CT scans from MRIs[14] and scoliosis radiographs from back photographs.[15]

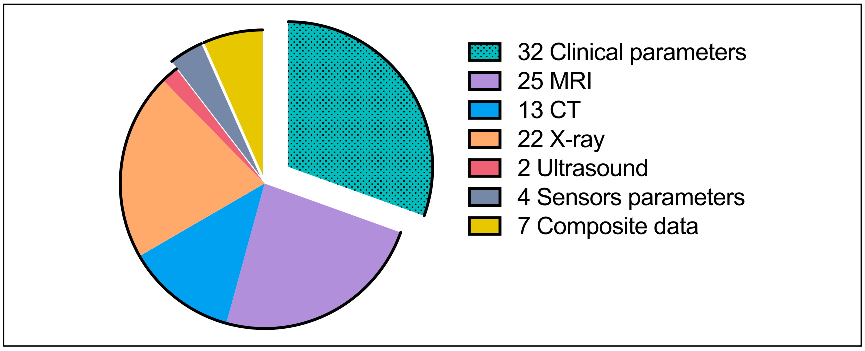
Four studies were conducted upon sensor-based parameters, with examples being radio frequency sensing for early diagnosis of spinal disorders,[16] gait acquisition with wearable inertial sensors for spinal cord injury

Figure 2



Visual representation showing country of origin of study corresponding author.

Figure 3



Pie chart showingsummary on the type of data used.

evaluation and prognostication,[17] hand movement video capture,[18] and smartphone-based grip-and-release parameters[19] for cervical myelopathy screening and severity evaluation.

Data Size

We investigated the cumulative size of assembled data sets and did not distinguish between training, validation, and testing sets because of variability in data division ratios. MRI and CT scans obtained at the same time point were considered as a single data belonging to one subject, rather than by dividing according to each two-dimensional slice. Data size among the literature was highly variable. As shown in Figure 4, 14 studies involved less than 100 subjects, 64 studies consisted of subject counts between 101 and 1,000, whereas 22 studies contained more than 1,000 but less than 10,000. Five studies reported more than 10,000 subjects, and among these, four studies used clinical parameters as model inputs and one study used radiograph images.

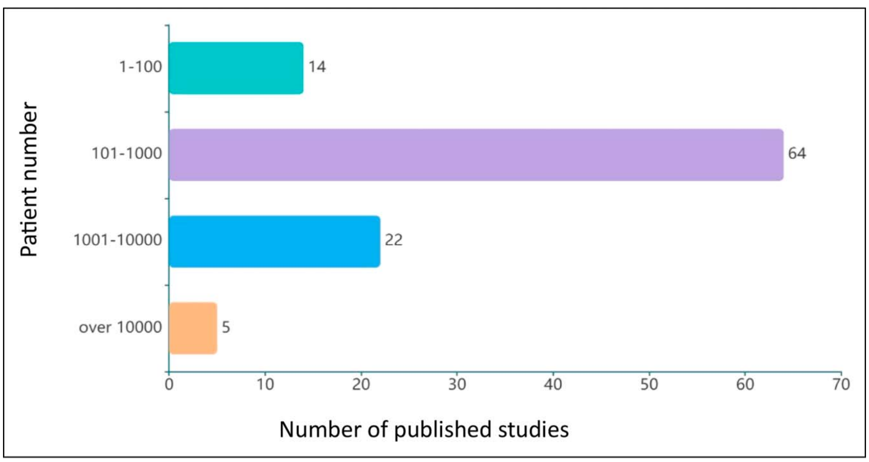
Independent testing with a separate data set is essential for AI model performance evaluation, and multicenter validation may be considered an ideal benchmark for real-world performance and generalizability. Overall, 72 studies collected data from a single center, whereas 23 studies used multicenter data for model development and validation. Ten studies used data from public databases.

Application of Artificial Intelligence in Spine Surgery

Medical Image Computing

MIC is an interdisciplinary field concerning computer science, information technology, and medical imaging. MIC uses computer-based techniques to analyze and interpret medical images, such as radiographs, MRIs,

Figure 4



Horizontal bar chart showingpatient number recruited for study data set.

CT scans, and ultrasounds. We outline several common modes of application below -

- SegmentationThe objective of image segmentation is to divide an image into segments that correspond to distinct anatomical structures or regions of interest, often in preparation for further focused analysis. Conventional manual segmentation techniques, in which radiologists or clinicians outline regions of interest, are labor intensive and subjective. By contrast, AI-powered segmentation offers an automated and standardized approach. Twenty-nine out of the 105 publications in this review specifically concerned MIC.
- Segmentation based on radiographsThe segmentation of radiographic images in spine surgery most commonly concerned the detection of vertebrae.[20] Precise identification and division of vertebrae can enhance the efficiency of diagnosing spinal conditions such as fractures and degenerative disk disease. This capability may be especially well-suited in the emergency ward and primary care environments where prompt assessments in the presence of nonspine specialists is crucial, for example, in the recognition of osteoporotic vertebral collapse in the elderly.[21]
- Segmentation based on CT images.CTs similarly enable for automated segmentation and labeling of vertebrae along the entire spine.[22,23] An example of application following segmentation is planning for stereotactic radiation therapy. More than 90% of automated treatment plans for bone metastases to the spine following model training was demonstrated to be viable upon evaluation by a radiation oncologist.[24] Another study achieved automated localization and segmentation of lumbar cancellous bone based on CT scans,[25] which may be the basis for the diagnosing osteoporosis or osteopetrosis based on Hounsfield units, and for the assessment of pedicle screw pullout strength.
- Segmentation based on MRI scansMRI scans are especially useful for segmentation of soft tissue such as intervertebral disks,[26-29] dural sac, nerve roots,[30] paravertebral musculature,[31] and bone marrow fat.[32] Pfirrmann grading for lumbar disk degeneration grade is determined by intervertebral height and signal intensity within the nucleus pulposus, whereas Modic changes dependent on vertebral bone marrow signal intensity.[33] AI-assisted disk and vertebra segmentation is a prerequisite to obtaining such measurements.[28]

Assisted measurement

Measurement of distinct parameters from spinal imaging is crucial for diagnosing various spinal conditions. AI-based algorithms can negate errors and expedient data collection in comparison to manual measurement.[34] Literature concerning assisted spinal parameter measurements may be categorized into four main areas.

- Vertebrae landmark detection and localizationAlgorithms have enabled for the localization and identification of cervical, thoracic, and lumbar vertebrae from CT scans,[35] which provide the foundation for diagnoses and therapy. An example is in the diagnosis of cervical instability through a U-Net-based algorithm identifying vertebral landmarks on dynamic cervical radiographs and thereafter calculating the relative angles of motion between adjacent vertebrae.[36]
- Cobb angle and spinal curvature measurementsUpon manual measurements, 95% confidence intervals for Cobb angles vary from 2.8° to 8°.[37] Conversely, upon AI-assisted measurements, the mean absolute error (MAE) was more consistent at $<3°$.[38-40] AI also facilitates measurement of spinal curvatures upon off-center, angulated, and blemished images, as well as from photographs captured from smartphones or screenshots.[41] Ultrasonic images have demonstrated utility for scoliosis screening by extracting landmarks (i.e. spinous processes) to build a three-dimensional spinal profile while avoiding radiation.[9] Another clinically relevant application is in the quantitative measurement of thoracolumbar compression fractures to facilitate management.[42]
- Spinopelvic parameter measurementAn accurate assessment of spinopelvic parameters is especially important for surgical planning in deformity correction toward improving pain and functional outcomes. In addition to Cobb angles, AI may be harnessed upon standing whole-spine radiographs to automatically measure spinopelvic parameters, including coronal vertical axis, sagittal vertical axis, thoracic kyphosis, lumbar lordosis, T9 spinopelvic inclination, frontal pelvic asymmetry, sacral slope, pelvic tilt, and pelvic incidence. Performance in both coronal plane (ICCs $\geq$ 0.95; MAE $\leq$ 2.9° or 1.97 mm) and sagittal plane-based (ICCs $\geq$ 0.85; MAE $\leq$ 4.4° or 2.7 mm) parameters demonstrated excellent consistency,[43] as was also demonstrated by another similar study.[44]
- Grading of disk herniation, central canal stenosis, and nerve root compressionFeatures and

parameters upon spinal MRIs are invaluable toward diagnosis of disk degeneration and neural compression. As examples of AI-assisted diagnoses, intervertebral disk herniation, central canal stenosis, and nerve root compression may be diagnosed by analyzing the size of the herniated disk, space occupied by cerebrospinal fluid, and the spatial relationships between the disk and the nerve root. The resulting accuracy for neural compression ranges from 81% to 84%, with respective κ values comparing expected and observed accuracy ranging 0.92 to 0.98.[45,46]

Diagnosis of Spine-Related Disorders

Segmentation provides a foundational reference for detecting spinal anomalies, and thereby facilitates the diagnosis of common spinal disorders as detailed below. In addition, the introduction of automated medical reports following imaging findings has been proposed to enhance diagnostic efficiency and costs by reducing the necessity for healthcare professionals while also minimizing the chance for error.[47,48]

Vertebral fracture

AI can detect variations in vertebral height, shape, and bone density, thereby facilitating the detection of vertebral fractures.[49-52] A DL classifier for osteoporotic fractures employed spinal radiographs to identify and categorize fractures based on the amount of vertebral height loss and was proposed as a potential screening tool.[53] Furthermore, AI has the potential to classify vertebral fracture subtype by AO classification, achieving an accuracy approaching 80%.[54] The Thoracolumbar Injury Classification and Severity Score is an assessment tool commonly used to facilitate the management of traumatic thoracolumbar spine injuries. A DL model was developed to allow for automated categorization of vertebral morphology and assessment of the integrity of the posterior ligamentous complex from CT scans.[55] Vertebral fractures may also be secondary to metastasis, and by analyzing imaging features such as the presence of soft-tissue masses and bony destruction, a model was trained to detect malignant vertebral fractures and make diagnostic recommendations.[4,56]

Scoliosis

Scoliosis is defined as a coronal deformity of the spine with Cobb angles of $\geq 10°$. AI can identify adolescent idiopathic scoliosis (AIS) by analyzing whole spinal radiographic images and measuring Cobb angles.[57] Given the concerns over frequent radiographic exposure, automated segmentation of ultrasonography images has been described to facilitate scoliosis diagnosis at the clinic.[8] In another approach, DL was applied upon a light-based depth sensing technology toward radiation-free AIS screening.[15] Separately a platform used software defined radio and noncontact radio frequency signals to detect abnormal coronal and sagittal spinal curvature with an accuracy rate of 99%.[16] AI-driven assessment of skeletal maturity indices, such as the Risser sign[58] or distal radius and ulna index,[11] facilitate decision making in AIS. ML clustering was implemented to classify scoliotic patients based on age, frailty, and mental health, which helped to reduce the heterogeneity of the scoliosis population studies and contribute to the development of individualized treatment plans.[59] Automated models for AIS screening and prognostication promise to triage referral time, follow-up intervals, and identify progressive curves for preemptive treatment.[11]

LDH and lumbar spinal stenosis (LSS)

Automated diagnosis from imaging of lumbar disk bulging and spondylolisthesis achieved an accuracy of more than 90% through MRI scans.[60] Clinically, however, LDH and LSS are diagnosed through symptoms, for example, of sciatica in the former disease entity, and neurogenic claudication in the latter. To overcome the caveat of reaching diagnoses based on lumbar spine MRIs alone,[61,62] a natural language processing algorithm was proposed to distinguish between LDH and LSS from symptomatology recorded in the admission record with an accuracy exceeding 75%.[63]

Ankylosing spondylitis (AS)

AS is a chronic inflammatory disease that predominantly affects the axial skeleton, including spine, pelvis, and hips. Detection of subtle radiological changes in the sacroiliac joint facilitates early diagnosis of AS and enables prompt treatment with disease-modifying drugs. A DL-based classifier was developed to detect bony erosion upon CT scans to diagnose AS resulted on sensitivity and specificity measures surpassing that of an experienced musculoskeletal radiologist by 8.4% and 9.5%, respectively.[7]

Spinal tuberculosis

Spinal tuberculosis remains prevalent in underdeveloped nations. The scarcity of medical resources and expertise with regard to radiological and microbiological diagnosis in endemic areas facilitates disease transmission. A computer-aided diagnostic system was developed to improve the effectiveness of radiological diagnosis of tuberculosis from lumbar CT scans obtained of patients from Tibetan regions of China, resulting in an accuracy of 98.3%.[64]

Ossification of the posterior longitudinal ligament (OPLL) and DCM

Diagnosing OPLL through radiographs alone is challenging. A convolutional neural network (CNN)–based DL approach was employed to detect cervical OPLL on plain radiographs, using CT scans as the reference standard. This demonstrated a diagnostic accuracy that was 20% better than that of spine surgeons.[65] Another study used ML upon cervical MRIs toward diagnosing OPLL and achieved an accuracy of 98%.[66] Separately, DCM is the largest cause of nontraumatic cervical cord stenosis in developed countries.[67] A study proposed smartphone-based video capture of the grip-and-release test followed by DL as a viable screening tool.[19] Finger kinetics were extracted from videos to allow for binary classification of DCM with sensitivity and specificity measures approaching 90%.

Spine tumors and spinal metastases

Distinguishing between benign and malignant vertebral fractures from CT scans can be a challenge, and an AI model demonstrated a high level of discrimination that matched or surpassed that of radiology residents (0.71 < area under curve [AUC] < 0.86).[68] In combination with clinical parameters (age, sex, tumor location), imaging can aid in differentiating benign intradural spinal cord tumors with an Area Under Curve — Receiver Operating Characteristics of 0.92.[12] In spinal oncology, precise segmentation is essential to delineate margins for therapeutic interventions such as radiation and surgery. In delineating the margins of involvement, trained models can facilitate in the grading of metastatic spinal cord compression.[3,69,70]

Osteoporosis

Dual-energy radiograph absorptiometry remains the benchmark for quantification of bone mineral density (BMD). Numerous publications have leveraged more readily available imaging modalities to extrapolate BMD.[6,71-74] A representative study from Taiwan contained 36,279 subjects who underwent dual-energy radiograph absorptiometry scans as well as hip and spine radiographs. External validation of the algorithm demonstrated its consistent and excellent ability to predict BMD from standard radiographs and classify patients with a 95% positive or negative predictive value with osteoporosis.[71] Several studies have focused on automated diagnosis of osteoporotic vertebral fractures using radiographs, achieving an accuracy of >0.9.[75-78] Automatic classification through the Assessment System of Thoracolumbar Osteoporotic Fracture has also been realized with an accuracy ranging from 69.2% to 87.5%.[79] Furthermore, MRI scans may be used as image input for the automated diagnosis of recent osteoporotic vertebral fractures (accuracy = 0.88, AUC = 0.94).[80]

Prognostication

Identifying Surgical Candidates and Predicting Outcomes

AI has been used to identify candidates with LSS who subsequently required surgery, based on axial cuts showing the severity of compression.[81] Other predictive outcomes included AIS curve progression,[11,82] blood loss in thoracolumbar burst fractures patients, spinal cord injury outcomes based on deviation in intraoperative mean arterial pressure,[83,84] fracture recurrence after vertebroplasty,[85] postoperative functional measures and mortality,[2,84,86-93] discharge timing and destination,[90,94-99] and risk of unplanned readmission.[100]

AI in perioperative risk management

In addition to predicting medical status–related postoperative complications such as prolonged hospitalization following spinal deformity surgery and postoperative delirium,[101] AI is also capable of predicting surgical complications including infection at the surgical site,[102,103] loosening of pedicle screws,[104] recurrent herniation following endoscopic disk removal,[105] and junctional breakdown.[106,107] Estimating the risk of such events all contribute toward optimizing patient care[18] and surgical decision making.[108] As examples on the application of ML to prognosticate using multimodal data, functional ambulation following incomplete spinal cord injury was predicted using demographic information, clinical measures, limb acceleration, and inertial sensors.[17,109]

AI's predictive capability in spinal metastases

Patients with spinal metastases and an unknown primary are required to undergo a full range of invasive diagnostic tests that can consume a great deal of money and time. CNN models can identify tumor features upon conventional spine MRI sequences and suggest the most likely site of the primary lesion (AUCROC > 70%).[110] AI also predicts intraoperative blood loss (AUC = 0.809)[111] as well as longer hospital stays and complications by considering preoperative medical and functional status in addition to tumor staging.[112] In addition, the capacity to regain ambulation is a factor influencing whether surgery should be offered, and AUC of a predictive model was approximately 90%.[113] AI may forecast treatment efficacy for stereotactic radiation by analyzing clinical characteristics and MRI data (AUC = 0.828).[13]

Surgical Planning and Assistance

AI assistance facilitates selection of appropriate implant size, as well as the course and length for screws.[114]

Intraoperative navigation of screw placement is also becoming common place. Their benefits include increased precision and enhanced intraoperative efficiency, markedly reducing complications and improving outcomes[115] while obstacles to more widespread integration include costs, additional preoperative investigations, and planning as well as learning curve.[116,117] Although navigation usually requires a preoperative CT scan, there has been a report of MRI-derived synthetic CT images for lumbar surgical planning as an alternative to reduce radiation exposure.[118] Postoperatively, AI can automatically perform measurements of screw trajectory for further analysis.[119]

Artificial Intelligence Learning Algorithms

Supervised Learning and Unsupervised Learning

AI learning-based approaches may be categorized into supervised and unsupervised learning. Supervised ML aims to identify patterns in a prelabeled data set to arrive at a desired outcome, whereas unsupervised ML models are given unlabeled data and allowed to identify patterns without any explicit guidance or instruction. The two approaches may also be combined in semi-supervised learning when labeled data are difficult to obtain. Most AI-based studies were conducted through labeled data sets with supervised learning (n = 100).

Machine learning and deep learning

ML is a branch of AI that applies algorithms upon data to imitate human learning and apply decision making on new and unseen data. Conventional ML commonly relies on manual or software-based feature engineering to extract analytical representations from raw data.[3] DL, a subset of ML, consists of a layered structure of artificial neural networks. Among included studies, 38 used traditional ML methods upon predefined features, whereas 67 used DL to automatically extract features.

ML tasks and algorithms

Twenty-eight studies concerned classification tasks for prognosis prediction, whereas five concerned classification tasks for spinal disease diagnosis or screening. Four ML-based studies regarded prognosis forecasting through regression with continuous (not binary or categorical) outputs. As an example, an ensemble ML model reported spinal cord independence measure using features present at the time of admission for rehabilitation.[92] One study with a mixed task definition reported, respectively, combining classification and regression for DCM screening.[111] One study reported using ML for spinal CT segmentation to reduce computing load with DL methods.[35]

ML-based studies commonly used multiple algorithms, reporting the one with the best performance. Algorithms with best prediction performance included random forest/decision tree (n = 13), gradient boost/XGBoost (n = 6), support vector machine (n = 5), and logistic regression (n = 3). Ensemble ML methods incorporate multiple algorithms to enhance performance and were reported in three studies,[13,92,113] whereas eight studies were based on other ML algorithms.

DL tasks and algorithms

For DL-based literature, 25 studies were defined as classification tasks, 30 studies as MIC tasks (landmark detection, objective detection, and segmentation), 10 studies as composite tasks, and two studies as medical image generation tasks. Among classification tasks, 23 studies concerned diagnosis, whereas two studies concerned prognosis for AIS curve deterioration.[11,82] In studies concerning DL-based MIC, 24 studies were for image segmentation, including 13 with resultant automated measurements. Five studies were there concerning landmark detection on radiographic images for automated measurements, and one study for object detection to identify LDH.[5]

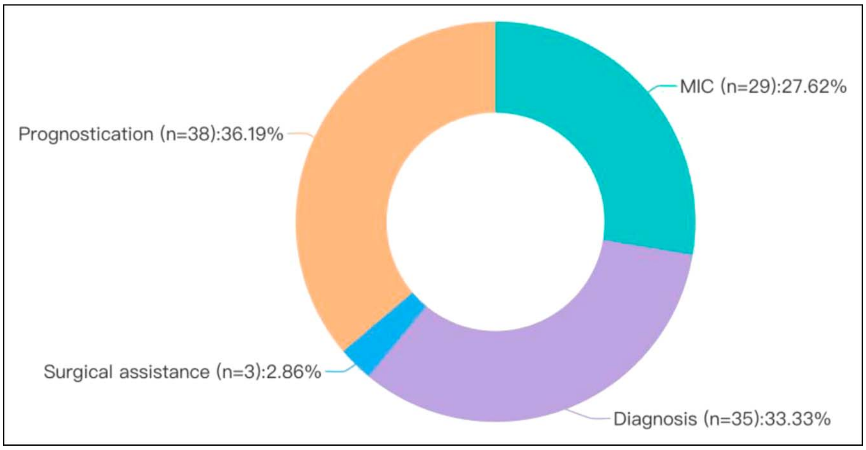
A natural language processing study used long short-term memory method to diagnose LDH and LSS from clinical records.[63] Otherwise, all other DL-based literature conducting medical image analysis with computer vision methods selected CNNs as the basic structure. As more than one DL structure may have been implemented, we quantified commonly reported DL structures. Among included studies, 39 studies used CNN structures and its variants, including Visual Geometry Group, ResNet, HR-Net, graph CNNs and attention-based CNNs. The U-Net family (n = 21) and Mask-RCNN (n = 3) were the most often used DL structures for segmentation tasks, whereas You Only Look Once (n = 5) and Fast/Faster-RCNN (n = 5) were used for object detection tasks. Vision transformer (n = 2) and generative adversarial networks (n = 2) were reported in the literature to address image segmentation and synthesis tasks. Four studies were there concerning ensemble learning to combine multiple DL models or composite inputs for enhanced prediction performance.

Discussion

The Present State of Artificial Intelligence in Spine Surgery

As summarized in Figure 5, the literature concerning AI in spine surgery predominantly concerned prognosis

Figure 5



Donut chart showingmode of application of artificial intelligence in spine surgery.

prediction (36.2%), diagnostic assistance (33.3%), and MIC (27.6%). Conversely, AI's application in surgical assistance appears underrepresented in academic literature (2.9%), likely because progress is of greater relevance to the industry sector and kept proprietary instead being disclosed.

With the focus on patient management, AI-facilitated diagnosis promises to create highly individualized treatment plans, which will be refined when models are developed upon larger, multicenter data sets.[120] From the standpoint of the healthcare provider, an automated workflow will diminish burden on the medical staff, permitting healthcare providers to allocate their expertise more judiciously. AI-facilitated prognostication promises to improve case selection for surgery and, in so doing, improve perioperative outcomes and ensure optimal resource utilization.[121] Intraoperative navigation, robotics, and augmented reality technologies will minimize procedural errors and enhance patient safety; however, they may best be selectively applied to complex cases to reduce expenses, in the hands of a surgical team familiarized with surgery of the relevant technology and its limitations.[122]

Assessing the Quality of Artificial Intelligence–Related Research

The exponential increase in scientific research concerning the application of ML across biology and medical disciplines has led to the imparting of recommendations to improve upon ML assessment and reproducibility.[123] Broadly speaking, these encompass data management (sample size and quality), optimization of the ML model (fitting, parameter tuning), model (interpretation of model, access to source code), and evaluation (provision of performance measures and comparison to other methods).

The AUC upon ROC curves, Brier scores, and prediction squared error are common means to describe the accuracy and discriminatory value of ML models. Calibration and reliability of the model are other performance measures to be cognizant of, which would otherwise result in underestimation or overestimation of risk.[124] Despite the "black box" nature of model training, biological feasibility with regard to the model input, architecture, and results also add weight to clinical application.

As a means to standardize reporting frameworks, guidelines, such as CONSORT-AI, have been proposed for prospective trials, and this is likely the way forward.[125] Although the clinical question and application would be best defined by a clinician, close collaboration with computer science experts in project planning, execution, and interpretation would be essential. The challenges of big data classification, processing massive data sets, caveats in supervised and unsupervised ML approaches, feature selection, model selection, and consideration of external validity have been summarized elsewhere.[126]

Limitations and Outlook

Like all innovations, AI's integration into spine surgery also has its challenges. The efficacy of an AI model is dependent on the quality and comprehensiveness of its training data set,[127] which would be incorporating a standardized pipeline for data collection and storage within routine clinical practice. Most studies included in this scoping review are retrospective. Furthermore, multicenter validation was lacking, with most data sources for AI training coming from a single hospital. The heterogeneity of input data offers a challenge for AI, especially when the clinical context, population, or disease is rare thereby presenting a data bottleneck.[128]

Conclusion

An increased incorporation of AI into clinical practice is inevitable and exciting. The present generation of clinicians needs to be aware of the potential and pitfalls of AI-related technology to selectively and effectively harness its benefits.

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