Artificial Intelligence in Orthopedics: A Concise Review

Abstract:

Artificial intelligence (AI) is attracting more and more attention as a potential tool in orthopedics. The purpose of this review is to catalogue and describe existing research in this area so that readers can grasp the breadth, depth, and nature of existing studies and be inspired to conduct their own. To summaries the application of AI in orthopedics, a concise review was carried out. Most research was conducted on the spinal column, the knee, and the hip. Artificial intelligence is increasingly being used in the field of orthopedics. Yet, the range of its therapeutic applications and the sub-specialty sections of the body that have been investigated to date remain restricted. Standardizing the way AI research is reported would facilitate objective evaluation and comparison. Validating AI systems for clinical usage requires prospective trials.

Keywords: artificial intelligence, machine learning, orthopedics, surgery.

1.1. Introduction:

Artificial intelligence (AI) applications have rapidly spread across the globe. Recommendation systems like Netflix, YouTube, and Spotify, search engines like Google, social-media feeds like Facebook and Twitter are just a few of the many modern applications of AI. AI has also made its way into the medical field. There is strong evidence that AI can perform as well as or better than humans at a variety of activities, including medical image analysis, symptom and biomarker correlation from electronic health records, and disease characterization and prognosis. Orthopedic surgery is one area where artificial intelligence has been successfully applied to enhance clinical decision making and patient care [1-3].

The pace at which technology is being incorporated into standard medical practice is astounding, and in few fields is this more apparent than in the field of orthopedic surgery. In many parts of the world, intra-operative input that is computer-guided, robot-assisted, and navigated in real time is now the norm. Interactive digital, semi-automated or fully-automated preoperative planning and template are also commonly available in many developed settings, and they are quickly replacing traditional two-dimensional imaging [1, 4-7]. John McCarthy coined the term "artificial intelligence" (AI) to describe the hypothesis that machines might one day be able to learn to perform human-level activities through pattern recognition with little to no human input[8, 9]. A more up-to-date and accurate definition of AI is the use of algorithms to give computers the ability to perform tasks that have historically required human intelligence. Jerrold S. Maxmen predicted in 1976 that artificial intelligence would usher in the "post-physician era" in the 21st century. Since its inception, artificial intelligence (AI) has gone from a theoretical concept to a practical tool with the advent of cheap computer power and the exponential growth of extraordinarily massive data sets ("Big Data") [10, 11].

To give just one example, deep learning (DL) is a subfield of machine learning (ML), which in turn is a subfield of artificial intelligence. The ultimate goal of artificial intelligence is for a computer (or other machine) to achieve human-level proficiency in a given task. The expansion of AI into the healthcare profession has been pushed by improvements in processing power, data storage, and the availability of high-quality data. Image identification, preoperative risk assessment, clinical decision making, and the analysis of enormous data sets are just some of the orthopedics-specific issues that are starting to be tackled by AI-based approaches[12].

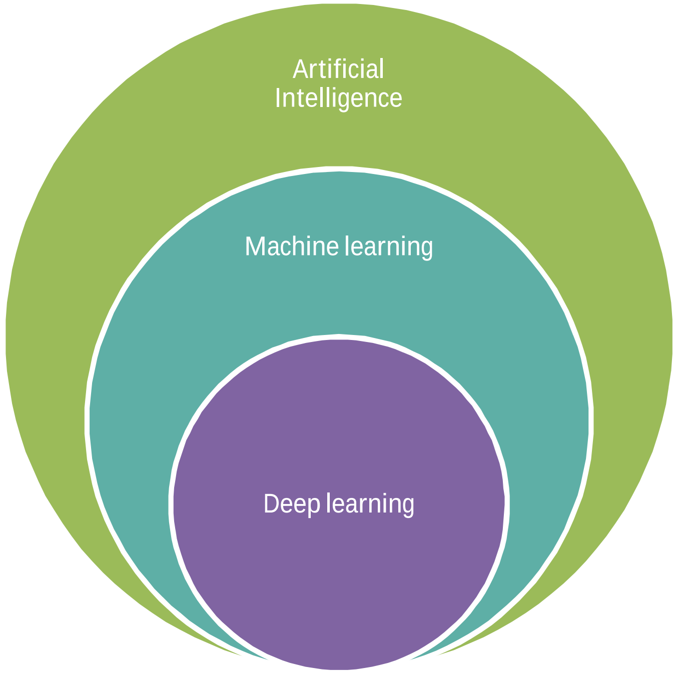

Figure 1 Representation that how Al, ML and DL are related

The entire medical imaging process, from image capture and reconstruction to analysis and interpretation, has benefited greatly from the application of AI methods. AI identifies the most appropriate patient-specific imaging examination and calculates the best appropriate procedure by incorporating information from the patient's medical records (including symptoms, laboratory results, and physical examination findings). Artificial intelligence (AI) has the ability to reduce the radiation exposure from computed tomography (CT) scans and speed up the collecting of data from magnetic resonance imaging (MRI) [13, 14].

2. Artificial Intelligence In Medical Sector:

Image interpretation is currently the most studied topic in artificial intelligence. Artificial intelligence (AI) is used in radiology to aid radiologists in making more accurate diagnoses and avoiding observer fatigue, rather than to replace them. Artificial intelligence (AI) algorithms have been used to diagnose a variety of conditions, including fractures, osteoarthritis, bone age, and bone strength. AI performs as well as or better than orthopedic surgeons in detecting fractures of the proximal humerus, hand, wrist, ankle, and vertebral compression fractures on radiographs AI also has potential applications in the automatic detection of hip or knee osteoarthritis on radiography, with performance comparable to that of The use of artificial intelligence (AI) in imaging is expected to increase and spread as new technologies are developed [13-15]. Clinical outcome prediction using a clinical dataset, genomic information, and medical pictures is another promising application of AI in healthcare. Clinical risk assessment and prognosis have always been difficult tasks. Artificial intelligence provides a fresh approach that may be able to solve these problems. Injury risk patterns associated with dynamic knee valgus can be predicted by analyzing visual and inertial sensor data using ML in orthopedics. Similarly, ML can be used to predict the rate of post-operative problems after lumbar fusion surgery for individual patients [16-18].

2.1. Artificial Intelligence In Orthopedics:

In recent years, a growing number of projects have emerged to use AI to solve difficulties unique to the orthopedic field. Recently, Cabitza presented a comprehensive systematic assessment of ML approaches used to orthopedic problems during the past two decades. The most common ML applied techniques were DL and support vector machines (SVMs), while the most common research topics were imaging of bone and cartilage, OA detection and prediction, and spine pathology. By a large margin, the most frequently used source of input data was medical imaging data [19]. We present a table with some significant instances of AI-related efforts in orthopedics, although a detailed study of these projects is outside the scope of this paper.

The use of AI can aid the doctor in making a determination or diagnosis. IBM Watson Health (IBM Corp., Armonk, NY, USA) is a cognitive computing system designed to improve diagnostic accuracy and reduce costs associated with cancer treatment by utilizing big case volumes and ML methods. Recommendations for the diagnosis and treatment of low back pain are also provided by clinical decision support systems. These systems can classify subjects, and future advancements may allow the combination of AI and clinician to create more stringent classifications than human decision-making alone. Hence, artificial intelligence (AI) may one day allow for more precise allocation to services, while also improving the availability and efficiency of self-referral [20-22].

Table 1 Some studies related to use of AL in orthopedics

Sr.	Applications of Al	Reference

1.	Automatic identification of adolescent idiopathic scoliosis through optimization of a three-dimensional spine model vector.	[23]
2.	Radiographic image analysis for fracture diagnosis.	[24]
3.	In order to make accurate clinical forecasts in the future, ML-based predictions for physician order input have shown that it is preferable to priorities smaller amounts of more recent data over bigger amounts of older data.	[25]
4.	dual-energy x-ray absorptiometry for the prediction of hip fractures.	[26]
5.	The mechanical performance of a short-stem total hip replacement can be improved by using machine learning techniques.	[27]
6.	New York University uses a value-based care-aligned artificial intelligence system (PersonaCARE) to manage its middle-aged and elderly fracture population.	[28]
7.	Having concluded that the current value-based bundled care approach to hip fractures is unsustainable,	[29]
8.	Joint replacement of the lower extremities: expected hospital expenditures, duration of stay, and patient outcome.	[30]
9.	Articular cartilage thickness in MRI of healthy knees, automatically measured and segmented	[31]
10.	Estimation of Complications and Mortality Rates 30 Days After TJA	[32]

11.	Predicting in-house SNF utilization after TJA with ANN using internal EMR data.	[33, 34]
12.	Using ML before TJA surgery to determine which patients have a good chance of experiencing MCI is a promising area of research.	[34]
13.	Infections at orthopedic surgery sites can be detected using natural language processing.	[35]
14.	Excellent summary of the use of AI and ML in spine studies.	[1]

It wasn't until the ROBODOC system for preparing and performing complete hip replacement became available in 1992 that robotic technology was first used in orthopedic surgery. Recent years have seen significant development in the application of robots. Unilateral knee arthro-plasty, total knee arthro-plasty, and total hip arthroplasty are typical applications for orthopedic robots like the Mako system. A study shows that robots are more effective than traditional methods for establishing limb alignment and shortening surgical procedures with minimal blood loss [36]. The Renaissance robot and the Rosa robot have been the focus of the vast majority of spine surgical research. Many studies have shown that as compared to traditional surgery, robotic procedures result in greater pedicle screw precision and less radiation exposure for patients and medical personnel. However, the low cost-effectiveness and limited indications for robotic surgery may restrict its wider clinical implementation [37-40].

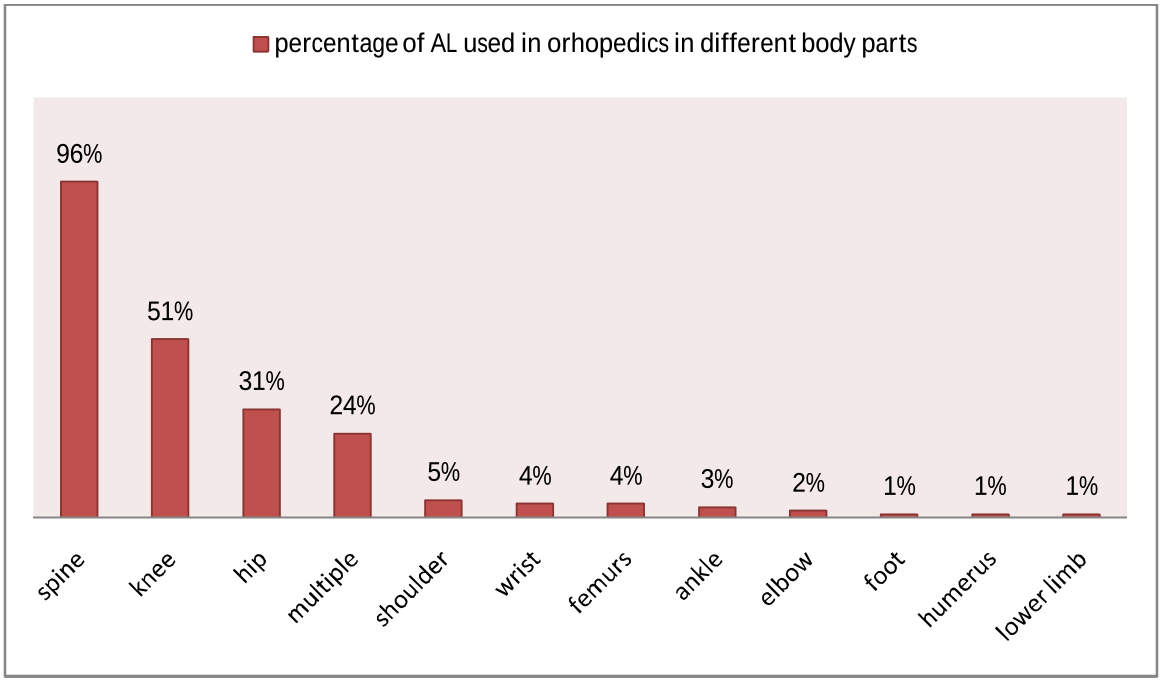

Fig 2: Percentage Of Al Used In Orhopedics In Different Body Parts

The field of orthopedic surgery has been radically altered by AI, yet it is still far from ubiquitous or ideal. Artificial intelligence does have its drawbacks. First, there are barriers to the widespread use of AI due to its prohibitive upfront cost, the length of time required for its usage (during pre- and post-operative phases), the unpredictability of AI technology reliability, and the lack of long-term follow-up research. This means cutting down on the time and money needed to implement the AI technology and conducting more comprehensive long-term research. Second, there are moral issues to think about when applying ML to orthopedic surgery [41, 42]. Without proper protections in place, working with large datasets raises the possibility of violating patients' privacy and consent, especially in situations when patient interests and business interests are at odds [43, 44]. It is also not clear who should be held accountable in the event of a wrong diagnosis or botched surgery: the human surgeon or the robotic assistant. Therefore, it is crucial that ML is carefully investigated, managed, and verified. Third, some individuals have doubted the use of AI because surgical robots and the AI technology can only be employed for relatively simple procedures and have minimal autonomy and decision-making capacity in therapy [45, 46]. AI-assisted procedures have come a long way from their non-autonomous beginnings in robotics research and development, with scientists and engineers making significant strides towards task autonomy, conditional autonomy, and ultimately full automation. In the future, machines that are capable of self-learning will be able to carry out jobs without human supervision [47, 48]. It's possible, though, those AI medical devices will make decisions that humans can't control or override. Third, since AI in medicine is still relatively new, there is a chance those patients' rights will not be protected because technological progress always seems to come first [49-52].

2.1.1. **Joint Reconstruction:** It should come as no surprise that research into the use of artificial intelligence in the orthopedic field has focused heavily on the field's growing field of joint reconstruction. Imaging analysis for automated diagnosis, implant appraisal, and clinical outcome prediction are all examples of where AI has been put to use in joint reconstruction; other, more specialized uses include improving pre-operative workflow for patient-specific implants and implant R&D [53, 54].

2.1.2. **Spine:** According to the volume of academic literature, spine surgery is another one of orthopedics' primary areas of artificial intelligence study. Predicting postoperative complications and using imaging to diagnose spinal disorders are two of the most investigated areas [55, 56].

2.1.3. **Orthopedic Oncology:** Both primary bone and soft tissue malignancies, as well as metastatic illnesses, have been the focus of AI research in orthopedic oncology. Although the area is still in its infancy and has seen only a handful of clinical applications to date, promising outcomes have been reported in the literature [57, 58].

2.1.4. **Trauma:** Automated image-based fracture diagnosis is where orthopedic trauma AI applications now stand in the scientific field. Although it is still in its infancy, research on the use of AI to predict clinical outcomes for victims of trauma is beginning to emerge [59, 60].

2.1.5. **Sports Medicine:** Currently, AI is largely used for automated image-based diagnosis in the field of sports medicine. Since soft tissues like these are the most likely structures to be injured, magnetic resonance imaging is the preferred imaging method. Anterior cruciate ligament (ACL) and meniscal tear identification is the most common application in the study of knee injuries [61, 62].

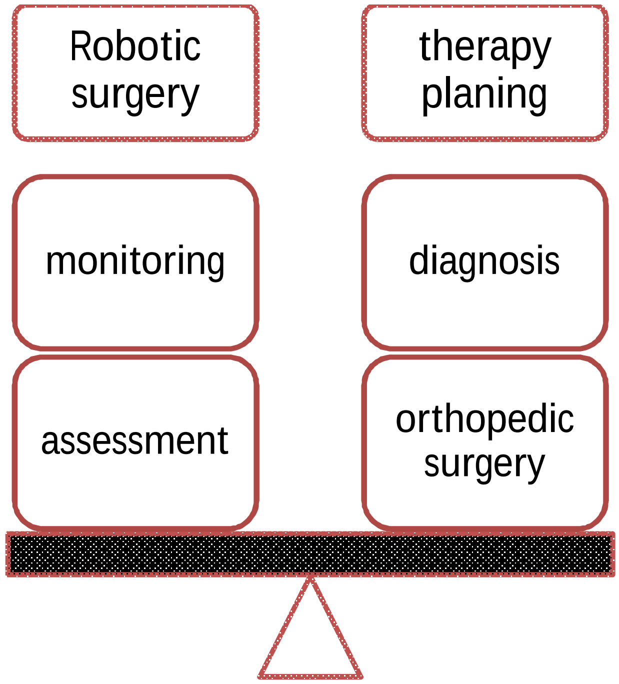

Figure 3: AL in orthopedics

3. Clinical Applications Of AL In Orthopedics:

Artificial intelligence (AI) in orthopedic surgery is increasingly being utilized, although still being seen as a 'new' topic by many. The availability of vast amounts of patient data, rising patient expectations for successful postoperative recovery and a collective determination to enhance the quality and precision of our care have all created fertile ground for the application of AI [63, 64]. Early targets of AI technology in orthopedics appear to be image recognition (diagnostics/implant identification, risk prediction, cost-outcome assessments, and clinical decision making. Positive results have been described in the areas of primary total knee arthro-plasty, primary total hip arthro-plasty (THA) and resurfacing [65], and primary total shoulder arthro-plasty (TSA)[65-69].

Artificial intelligence has been used and reported on in preoperative settings, namely in the areas of length-of-stay [66, 68, 70], and episode-of-care cost prediction, with 'good' validity in each case. It has been proven that early versions of this method for grading osteoarthritis from plain radiographs are just as accurate as those of arthroplasty surgeons with fellowship training, but much faster [71]. The accuracy of 3D templating and operative planning has reached 90% or greater compared to just 56.7% [72] for conventional acetylcholinesterase inhibitor (CAI)-based acetylcholinesterase inhibitor (CAII) recognition(including fractures), thanks to recursive feature elimination where training datasets can be refined to allow more 'targeted' feature-of-interest recognition (thus reducing image feature 'noi Predictions of where patients would go after receiving a THA, the chance of needing a long-term opioid prescription following THA, and the probability of requiring a blood transfusion following TKA have also been published with positive results [73]. Web-based program with even more user-friendly interfaces have been tested in real-world clinical settings for predicting discharge destination and the likelihood of requiring an RBC transfusion [68, 70, 74-78].

Per prosthetic joint infection was diagnosed using AI's automated image processing against the Musculoskeletal Infection Society (MSIS) standard; peri-prosthetic fracture classification was performed using the Vancouver classification, with a claimed sensitivity of 100 and specificity of 99.8 percent; and peri prosthetic component loosening of both THA and TKA constructs was diagnosed with an overall accuracy of 88.3 percent [79]. Automated postoperative monitoring and outcome assessment, risk prediction, and the likelihood of dislocation after primary THA have all been shown to be useful, as has the overall prospective determination of the need for TKA revision in a large cohort of 25,104 patients after the primary procedure. The final outcome and patient satisfaction can be predicted and/or improved with the use of apps that are already in use in research or early clinical use [78, 80-86].

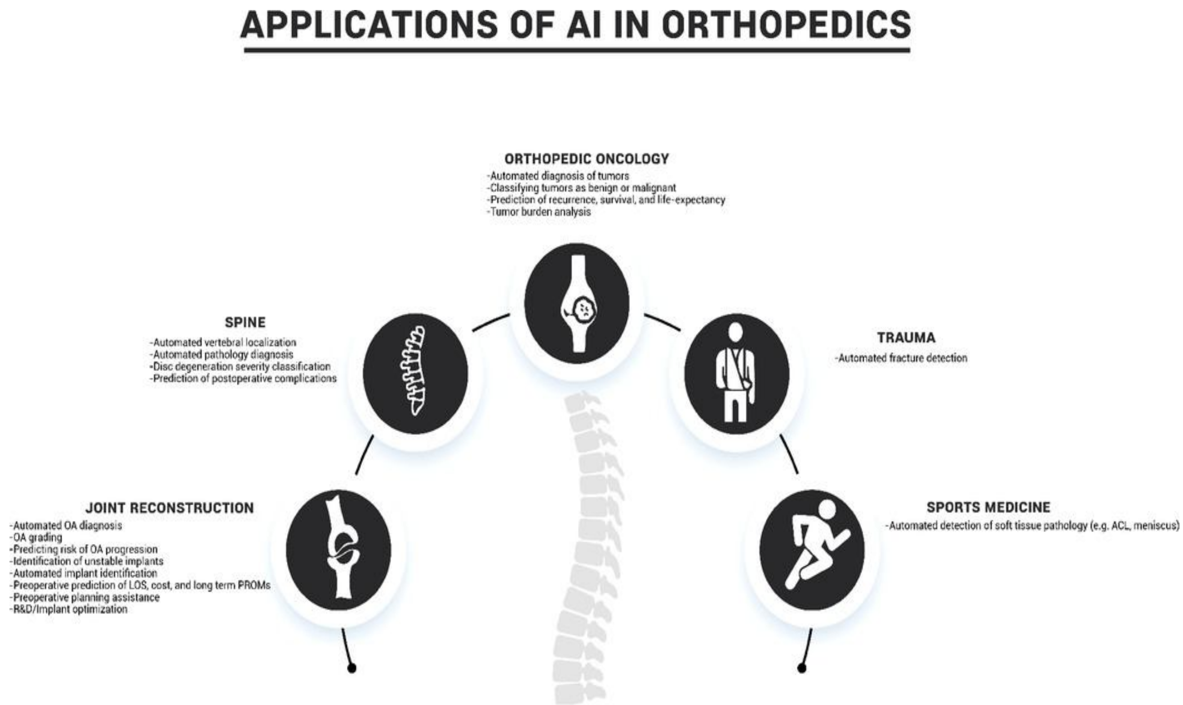

Figure 4 Applications of AL in orthopedics[87]

Conclusions:

The demand for medical resources rises sharply as people's incomes and standard of livings rise, but the supply of medical resources, doctors at the centre, is unable to keep up. Since computing power continues to increase exponentially, the shift towards digital health records cannot be stopped. The ever-evolving state of AI technology now allows for the meeting of these requirements. AI can aid clinicians in making diagnoses and determining prognoses by using the advantages of ML and deep learning in data processing. AI has the potential to significantly improve the clinical treatment outcomes in orthopedics, particularly in imaging-reliant specialties like orthopedics, by aiding in the analysis and judgment of pathology, assisting the surgeon in determining the optimal surgical path, and reducing surgical errors. While AI's demonstrated benefits are undeniable, it's important to acknowledge the field's current limitations. One of AI's key selling points is the massive amounts of data it can crunch. However, the medical device sector's current progress towards gathering health data is minimal at best. High-priced and high-priced AI features are defined by the present context. AI, on the other hand, is more suited for the treatment of more frequent diseases than unusual diseases because its ML concept is based on the learning of big sample data. AI also has to deal with a slew of issues, such as whether or not it will lead to physician burnout and apraxia and whether or not it will adhere to regulatory ethics in making decisions. In the field of orthopedic clinical practice, AI has demonstrated promising results and high value. Artificial intelligence (AI) could one day be used as a standard part of medical practice. To consistently achieve innovation and breakthroughs, more deep learning frameworks and deep learning systems are developed, improved, deployed, and used. Intelligent and well educated orthopedics is the future.

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