Artificial Intelligence in the Management of Anterior Cruciate Ligament Injuries

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Background: Technological innovation is a key component of orthopaedic surgery. With the integration of powerful technologies in surgery and clinical practice, artificial intelligence (AI) may become an important tool for orthopaedic surgeons in the future. Through adaptive learning and problem solving that serve to constantly increase accuracy, machine learning algorithms show great promise in orthopaedics.

Purpose: To investigate the current and potential uses of AI in the management of anterior cruciate ligament (ACL) injury.

Study Design: Systematic review; Level of evidence, 3.

Methods: A systematic review of the PubMed, MEDLINE, Embase, Web of Science, and SPORTDiscus databases between their start and August 12, 2020, was performed by 2 independent reviewers. Inclusion criteria included application of AI anywhere along the spectrum of predicting, diagnosing, and managing ACL injuries. Exclusion criteria included non-English publications, conference abstracts, review articles, and meta-analyses. Statistical analysis could not be performed because of data heterogeneity; therefore, a descriptive analysis was undertaken.

Results: A total of 19 publications were included after screening. Applications were divided based on the different stages of the clinical course in ACL injury: prediction (n = 2), diagnosis (n = 12), intraoperative application (n = 1), and postoperative care and rehabilitation (n = 4). AI-based technologies were used in a wide variety of applications, including image interpretation, automated chart review, assistance in the physical examination via optical tracking using infrared cameras or electromagnetic sensors, generation of predictive models, and optimization of postoperative care and rehabilitation.

Conclusion: There is an increasing interest in AI among orthopaedic surgeons, as reflected by the applications for ACL injury presented in this review. Although some studies showed similar or better outcomes using AI compared with traditional techniques, many challenges need to be addressed before this technology is ready for widespread use.

Keywords: anterior cruciate ligament; imaging and radiology; general; physical therapy/rehabilitation; injury prevention; gait analysis

Artificial intelligence (AI) is a branch of computer science that involves human-like learning systems. The term was first defined during a conference in 1956 by John McCarthy who referred to this technology as "the science and engineering of making intelligent machines."[12,13] This new theory came with dozens of different subfields, including machine learning (ML), whereby algorithms acquire knowledge via exposure to historical examples.[12,13,18] This knowledge acquisition can happen using either supervised or unsupervised algorithms. Supervised learning involves training an algorithm using previously labeled data to form associations, whereas unsupervised algorithms search for complex novel associations within unlabeled data.[12,13,18] Both forms of ML have garnered widespread application over the past decade, with common applications including search engine optimization and facial recognition software.[12,13,18]

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In medicine, AI can be applied either virtually using computers or physically using robots.[12] Over the past decade, the development of AI applications in orthopaedics has focused primarily on diagnostics, mostly image interpretation.[12,13,18,23] A recent study by Chen and Asch [9] demonstrated that a convolutional neural network (CNN), a type of ML algorithm, outperformed general orthopaedic surgeons at detecting and classifying proximal humeral fractures while performing similarly to subspecialized shoulder surgeons. In a similar investigation, a CNN was developed to interpret hand, wrist, and ankle radiographs with an accuracy matching that of senior orthopaedic staff.[31]

In orthopaedic sports pathology, close to half of all injuries involve the knee.[30] Of these injuries, tears of the anterior cruciate ligament (ACL) are frequently encountered, with noncontact ACL injuries making up to 78% of all sport-related knee pathology.[26] Although common, the diagnosis of clinically significant ACL injuries can be challenging for clinicians. ML may facilitate this by providing ways of addressing the variability of certain clinical tests, such as the pivot shift, while improving the diagnostic accuracy of magnetic resonance imaging (MRI).[4,36] However, along with improving diagnostics, AI may also serve to provide more robust solutions to other issues relating to the management of ACL tears. The accurate prediction of individuals at risk of ACL injury or reinjury, the identification of complex anatomic landmarks intraoperatively, and the optimization of pain control and rehabilitation protocols postoperatively present unique challenges that are well suited to ML modalities.[14,34,39,43] The purpose of this systematic review was to present how ML, with its ability to assess complex nonlinear relationships, has been used to address and improve the detection, treatment, and rehabilitation of individuals with ACL injuries.

METHODS

A systematic review was performed according to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines.[28] The search was performed in PubMed, MEDLINE, Embase, Web of Science, and SPORTDiscus databases between their start and August 12, 2020. The keywords used in the search were “knee ligament” OR “ACL” OR “anterior cruciate ligament” AND “Artificial intelligence” OR “machine learning” OR “learning algorithms” OR “deep learning” OR “learning machines.” Inclusion criteria included application of AI anywhere along the spectrum of predicting, diagnosing, and managing ACL injuries. Exclusion criteria included non-English publications, conference abstracts, review articles, and meta-analyses. After duplicate records were excluded, 2 reviewers (J.C. and J.P.L.) screened titles and abstracts for eligibility. All remaining manuscripts were then reviewed. Additional publications were selected by screening the reference lists of included articles. The AI models used in the selected studies are briefly explained in Figure 1.

Because of the heterogeneity in the data and the variability in study methods, statistical analyses of outcomes were not possible. A comprehensive review of the clinical applications and feasibility of AI with regard to ACL injury is presented.

RESULTS

The systematic search resulted in 184 articles. After removing duplicates, 121 articles were screened based on title and abstract. After reviewing the bibliography of each paper, 3 more articles were found to be eligible for this review. A total of 19 articles remained relevant based on the inclusion and exclusion criteria. The studies were divided based on the different stages of the clinical course: prediction (n = 2), diagnosis (n = 12), intraoperative application (n = 1), and postoperative care and rehabilitation (n = 4). A flowchart of the study inclusion process is shown in Figure 2, and a summary of the 19 included studies is available in Appendix Table A1.

Prediction

Johnson et al[16] developed an ML algorithm capable of predicting the risk of knee injury. Their pretrained CNN assessed 3-dimentional (3D) knee joint movements associated with ACL injury using marker-based motion capture while athletes performed 3 sport-related movements (walking, running, and sidestepping). This technology was compared with traditional biomechanical assessment using embedded force plates and a linear regression analysis. A high degree of correlation was observed, with the strongest correlation ($r = 0.8895$) occurring during the initial stance phase of sidestepping. The authors proposed that the ability to accurately predict knee joint movements from motion data may serve as an initial step in developing methods for real time on-field risk assessment for knee injuries, including ACL tears.

Pedoia et al[35] generated an AI algorithm capable of extracting and comparing differences in the tibial and the femoral bony morphology between normal ACL and ACL-injured knees. Using 3D MRI-based statistical shape modeling, they concluded that the relative distance between the condyles and the tibial plateau slope was a reliable landmark to differentiate normal and ACL-injured knees. The results, which are consistent with previously known morphological risk factors, highlight the potential for statistical shape-modeling algorithms to accurately detect anatomic risk factors for ACL injury, which may have implications for risk assessment in the future.

Diagnosis

Multiple investigations have applied ML to optimize both clinical and radiographic diagnosis of ACL injury.[§] Pertaining to clinical assessment, Labbe et al[19] developed support vector machines (SVM) able to objectively grade the pivot-shift phenomenon using algorithms that measure the relative movement of sensors placed on the femur, tibia, and iliac crest. These were compared with clinical grading by experienced surgeons using the International Knee

[§] References 5, 7, 19, 21, 22, 27, 29, 38, 42, 47, 48.

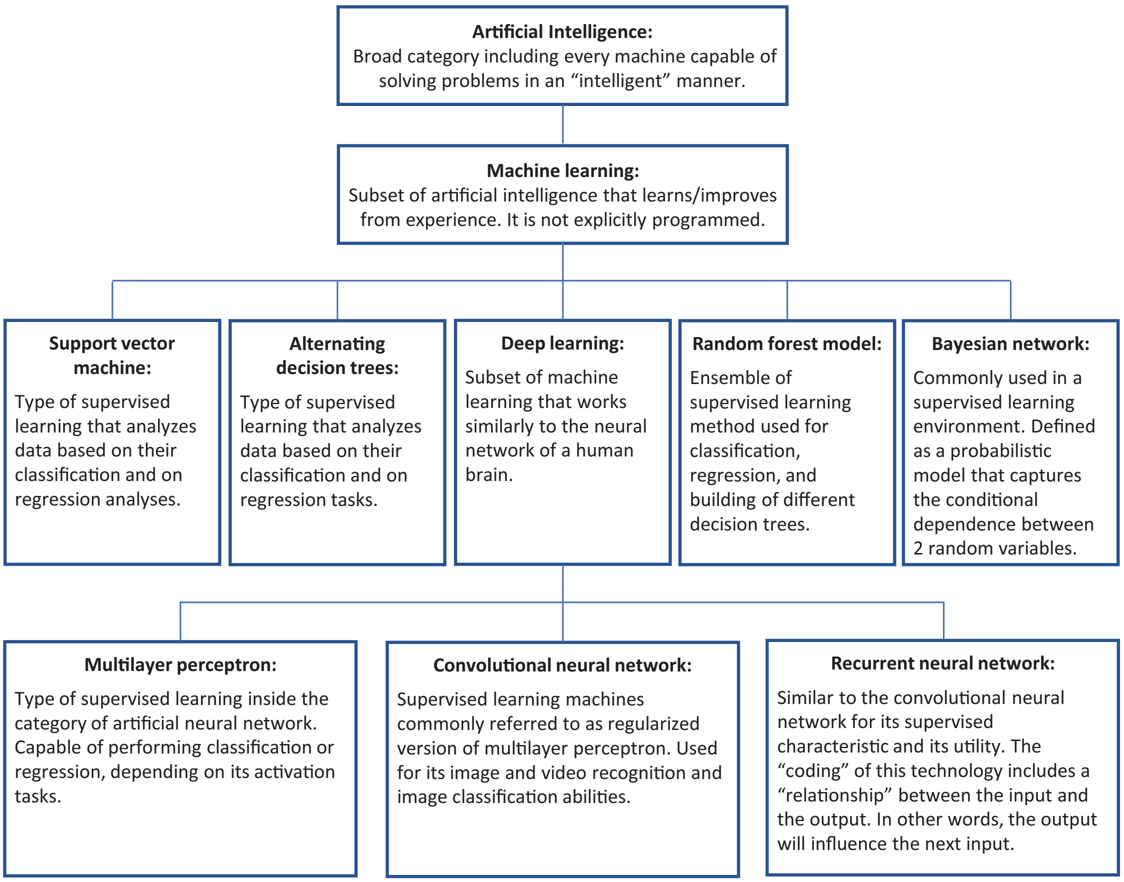

Figure 1. Description of the commonly used artificial intelligence models in the management of anterior cruciate ligament (ACL) injury.

Documentation Committee criteria. The results showed a significant agreement among clinicians in grading the pivot shift subjectively ($\kappa = 0.83$, considered "almost perfect") as well as a significant agreement using the SVM-established grades ($\kappa = 0.81$). There was also a near perfect agreement between surgeons' grading and the SVM-established grades ($\kappa = 0.83$, 0.79, and 0.82 for clinicians 1, 2, and 3, respectively). Furthermore, the SVMs were able to distinguish grades 0 and 1 from grades 2 and 3, with a sensitivity of 86% and specificity of 90%. The use of SVMs to interpret the pivot-shift test allows for an objective reference point for a test that is subject to a high degree of variability, especially in the hands of less experienced clinicians.[41] Li et al[21] developed another method to detect ACL injury using plantar pressure monitoring during the gait analysis. A 2-m pressure carpet with 16,384 sensors was used to record pressure data from both normal and ACL-deficient knees. A total of 100 data sets were collected, and 80 of these were used to develop an SVM. The remaining 20 were used to test and evaluate the accuracy of the SVM. In the final identification test, the overall accuracy of the SVM to identify ACL injury was 50% when considering both legs: 76% for the left leg and 62% for the right leg.

Despite several investigations examining the role of ML to optimize clinical assessment, a larger body of research has focused on the application of AI to assist in radiologic diagnosis. Bien et al[5] used a deep learning algorithm to diagnose ACL and meniscal injuries or detect general abnormalities on MRI scans. The model was trained using 1130 knee MRIs, fined-tuned, and then tested against an internal validation set of 120 examinations. The final prototype had a specificity of 0.968 for detecting ACL tears, similar to that achieved by general radiologists (0.933). However, the model had a lower sensitivity (0.759) compared with radiologists (0.906). In the detection of meniscal tears, general radiologists had significantly greater sensitivity compared with the model (0.892 vs 0.741). When clinicians used the model to assist in diagnosis, there was a statistically significant improvement in specificity for identifying ACL tears ($P < .001$), with a mean increase in specificity (0.048). In the proposed validation model that included 62 examinations, this translates clinically to 3 fewer patients potentially being indicated for surgery because of a false-positive diagnosis of an ACL tear. Moreover, all 120 models were analyzed within 2 minutes, compared with 3 hours required for radiologists.

Chang et al[7] tested a similar model by using a CNN to first crop the MRI scan to localize the ACL and then identify the presence or absence of ACL tears. The model's accuracy was studied using 1, 3, and 5 slices per knee. The

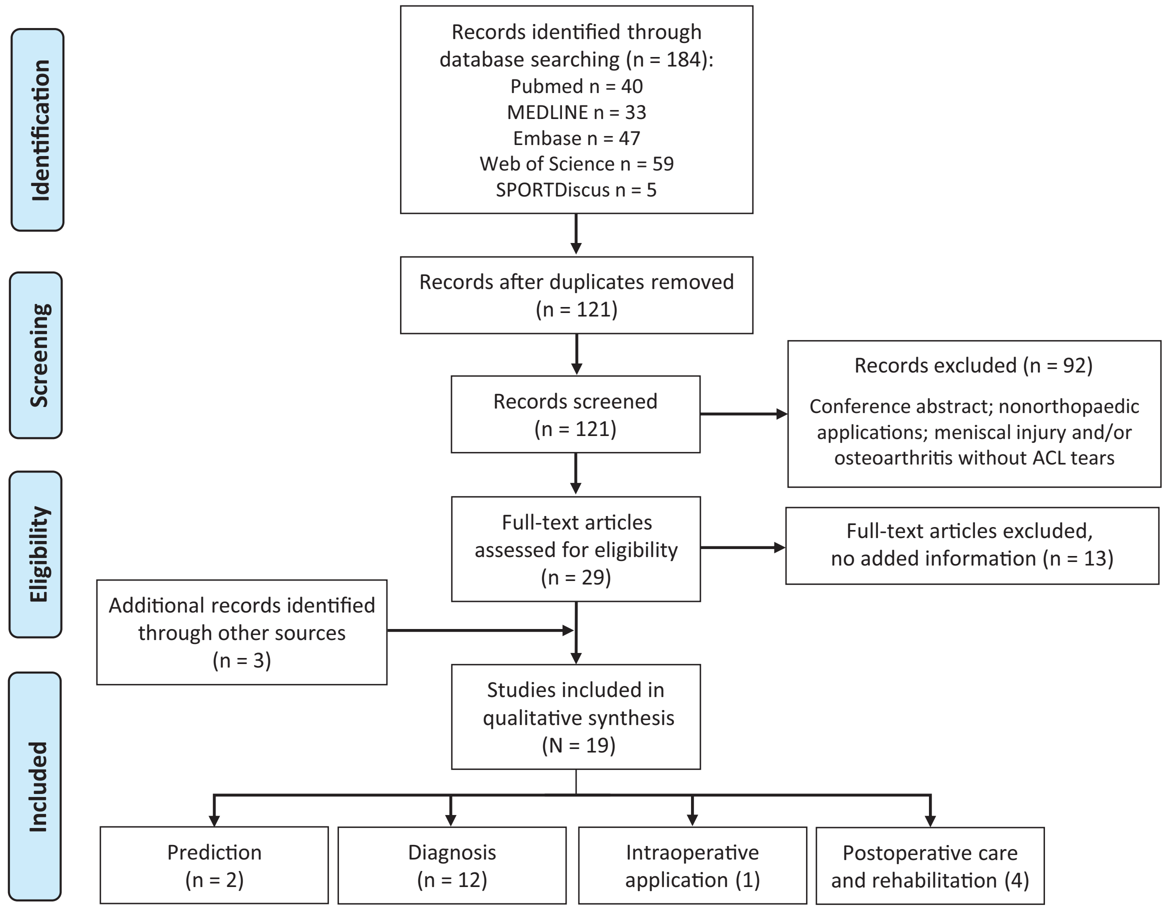

Figure 2. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram.

results illustrated that the algorithm performance improved in proportion to the number of input slices. The corresponding sensitivity, specificity, positive predictive value, and negative predictive value of the 5-slice model were 0.940, 0.890, 0.895, and 0.937, respectively. Similarly, Liu et al[22] used 2 CNNs to isolate the ACL on MRI images and identify the presence of a complete ACL injury tear. The reference for the final diagnosis was determined using arthroscopy. The results revealed that there was no statistically significant difference in the detection of ACL tears between the designed algorithm (sensitivity, 0.96; specificity, 0.96) and the 5 radiologists (sensitivity, 0.96-0.98; specificity, 0.90-0.98). ML may also serve to answer more complex diagnostic questions regarding ACL injury. Štajduhar et al[40] developed an SVM capable of detecting the presence of milder and complete ACL rupture. The statistical analysis results demonstrated that the SVM had an area under the curve of 0.894 for the injury detection problem and 0.943 for the complete rupture detection problem. These results suggest a potential role for computer-aided decision making not only for detecting ACL rupture but also for distinguishing between complete and partial tears.

Along with the diagnosis, AI has also been used to assist with establishing imaging protocols. Richardson[38] used CNNs to demonstrate that the use of ML can be an acceptable surrogate to human readers when performing a protocol optimization study for assessing the ACL tears on knee MRI scans. Two different types of MRI scans were used as input into the CNN: non–fat saturated (NFS) and fat saturated (FS). The receiver operating characteristic area under the curve for NFS and FS CNNs was 0.9983 and 0.9988, respectively. Specificity was identical for both NFS and FS images (0.993). There was a statistically significant difference in FS and NFS sensitivity (0.98 and 0.88, respectively; $P = .0253$). Based on these results, the author concluded that a CNN could serve as a reliable surrogate for a human reader when assessing the large number of scans needed for MRI protocol development, while eliminating the potential for bias and fatigue.[38]

Intraoperative Application

As of the date of the most recent search conducted for this review, a single ML application has been developed for intraoperative use in knee arthroscopy. To provide additional contextual awareness for surgeons, an algorithm capable of automatic segmentation of the arthroscopic frame was developed by Jonmohamadi et al.[17] The algorithm, "U-NET," is a CNN that was specifically created for the segmentation of biomedical images. This technology uses the arthroscopic video as an input parameter to produce a segmented image of the structures seen in real time by the surgeon. Using 3868 images collected from 4 cadaveric experiments and 5 knees, the authors programmed it to recognize key structures seen during knee arthroscopy: the femur, the ACL, the meniscus, and the tibia. The results obtained from this study were promising, with mean Dice similarity coefficients for the femur, the tibia, the ACL, and the meniscus of 0.78, 0.50, 0.41, and 0.43, respectively. The authors suggested that automated segmentation and tissue labeling could have important implications for both human surgical training and tool tracking in future robotic arthroscopic applications.[17]

Postoperative Care and Rehabilitation

Several studies focusing on ML applications for postoperative care and rehabilitation after ACL reconstruction have been conducted.[2,37,39,43] Rashkovska et al[37] generated an ML algorithm to predict internal knee temperature during therapeutic cooling (cryotherapy) after ACL surgery, which can be highly variable among patients. Using computer simulation, they were able to develop a model that could predict internal knee temperature using 4 temperature sensors placed on the skin. When their algorithm was tested using real external knee temperatures recorded during an earlier investigation, there was strong agreement between the internal knee temperatures predicted using ML and their actual in vivo measurements. This study highlights a potential role for AI to assist in determining the efficacy of postoperative cryotherapy, which may be used to develop personalized cooling protocols.[37]

Another predicting modeling tool was used by Anderson et al[2] to identify patients at a high risk of prolonged opioid use (>90 days postoperatively) after an ACL reconstruction. Using the patients' charts, they developed 4 models: logistic regression, random forest, Bayesian belief network, and gradient boosting machine. Based on the area under the curve and the Brier score, the gradient boosting machine model was considered the most accurate algorithm for this prediction. Results showed that it had a Brier score of 0.10 (95% confidence interval, 0.09-0.11) and an area under the curve of 0.77 (95% confidence interval, 0.75-0.80). Clinically, this prediction tool can improve shared decision making by providing a single, objective score that can be easily understood by the patient and the surgeon regarding the risk of excessive postoperative opioid use. Education about controlling postoperative pain before opioids along with recognizing those who may benefit from other pain control adjuncts could reduce the problem of opioid abuse, especially in patients at risk.[2]

Tighe et al[43] examined the ability of ML algorithms to predict which patients would require a femoral nerve block (FNB) post-ACL reconstruction. Several different ML classifiers were developed to identify a variety of pre- and perioperative factors present in patients' charts (eg, sex, tobacco use, perioperative nonsteroidal anti-inflammatory drugs, and ketamine use) and determine their association with postoperative pain and need for FNB. Using the receiver operating characteristic analysis, it was found that each algorithm outperformed the standard logistic regression, with an alternating decision tree having the greatest area under the curve (0.7), demonstrating a potential novel application of this technology for assessing patients who may benefit from FNB.

The potential of ML to assist with rehabilitation after ACL reconstruction has also been examined. Richter et al[39] used 8 cameras and 2 force platforms to objectively classify movement patterns between rehabilitating athletes after ACL reconstruction and athletes without ACL injury. Their goals were 2-fold: (1) find exercises that can accurately differentiate knees with reconstructed ACLs from normal knees and (2) determine the most appropriate type of ML for analyzing biomechanical data. They concluded that the double-leg drop jump had the highest classification accuracy (81%) and best predicted ACL injury using patternet, a neural network. These results suggest that AI algorithms are capable of interpreting complex biomechanical data from motion analysis to identify knees that have undergone ACL reconstruction, which may have important implications for postoperative ACL rehabilitation.

DISCUSSION

AI, and ML specifically, has the potential to revolutionize the field of orthopaedic surgery.[13] Nonetheless, only a handful of studies have examined applications for the management of ACL injuries. Presently, only 1 study[17] examining the intraoperative application of AI for knee arthroscopy has been published. However, future avenues for applications in ACL reconstruction exist, some of which are explored in greater detail in this section. The delayed adoption of this technology is likely multifactorial, with high development costs, complexity of use in absence of exposure or experience, and ethical considerations all playing a role.[9] Moreover, there is evidence suggesting that both health care providers and patients may distrust AI use in the health care setting.[18,23]

The focus of this systematic review was to provide readers with a summary of these investigations that have examined the application of AI in the management of ACL injury. As exemplified by the present review, much of the focus of ML applications for managing ACL injuries has been on improving diagnostic accuracy. Although seemingly trivial, the diagnostic reliability of some clinical tests is suboptimal. This was highlighted in a meta-analysis by Benjaminse et al,[4] in which a pooled analysis of 28 investigations demonstrated that the pivot-shift test had a sensitivity of only 24%. Furthermore, it was demonstrated that despite a high sensitivity and specificity for assessing chronic ACL injury, the sensitivity and specificity of the anterior drawer test decreased to 49% and 58%, respectively, when assessing acute tears.[4] In addition to these findings, there was only moderate interobserver reliability for the Lachman, anterior drawer, and pivot-shift tests when performed by professionals who are not orthopaedic surgeons.[36] This is important, as many of these individuals are the first to assess these patients and they are frequently responsible for initiating further work-up and expert consultation. The ML applications presented here, such as the work of Labbe et al[19] that employed SVMs to accurately grade pivot-shift tests, demonstrate the ability for these algorithms to introduce a higher degree of objectivity to the physical examination of the knee, especially for physicians and other medical professionals who are less familiar with this test.

Although there is little published literature on the integration of ML in clinical diagnosis, AI has been more extensively researched to aid in the interpretation of radiologic images, such as MRI.[13] Despite being heavily relied on for diagnosis and preoperative planning, MRI findings regarding ACL injury can be subject to a high degree of inaccuracy.[32] Multiple investigations presented in this review demonstrated the ability to train algorithms capable of not only assisting human diagnosis but also independently diagnosing ACL injury and other knee pathology with a high degree of accuracy.[5,22,40,48]

Deep learning also shows promise in MRI protocol optimization.[38] Protocol development usually requires radiologists to read multiple images at timed intervals to limit bias. Despite this, bias can still be introduced by the physician's personal preferences for certain protocols.[20] With increasing demands on productivity and efficiency, it can be difficult for radiologists to take part in time-consuming protocol optimization studies. To address this, Richardson[38] successfully trained a CNN as a surrogate reader to diagnose ACL tears from MRI scans with different pulse frequencies to successfully assist with protocol development. The rapid data interpretation purported by ML algorithms has also been highlighted by Bien et al[5] who reported a 90-fold increase in speed of MRI image interpretation compared with standard radiologists. This example highlights the potential for ML to assist in the diagnosis of ACL injury, minimize the time delay between image acquisition and interpretation, and theoretically accelerate diagnosis and treatment.

A potential application of AI could be in the assessment of graft status and integrity in the context of revision ACL reconstruction. In the event of a suspected graft failure, the decision to proceed with revision surgery can be challenging. In fact, it has been shown that physical examination, MRI, and arthroscopic evaluation do not always correlate when assessing graft integrity and failure,[44,45] further complicating decision making for the treating surgeon. ML applications could thus be used to integrate all of these data, create algorithms capable of improving diagnostic accuracy, and ultimately serve to facilitate surgical decision making in revision ACL surgery.

Despite significant advances in the implementation of ML in diagnosis, a more important role for AI may lie in risk prediction for ACL injury. The true power of this technology likely lies in its ability to form predictions from large preexisting data sets, lending itself well to prognostication using biomechanical data.[9] There is a significant body of literature examining the role of biomechanical factors and kinematic parameters in pathogenesis of ACL tears, some of which have been used to identify at-risk individuals.[15] However, because of the ability of ML algorithms to pick up complex, nonlinear relationships, this technology has the potential to extract even more important anatomic and biomechanical features that may predispose athletes to noncontact ACL injury. Presently, there are only 2 studies in the literature using ML in this manner. Although the work of Johnson et al[16] focused on monitoring all knee injuries, it is a good example of a CNN that can be used for the gait analysis to predict injuries. The imaging study by Pedoia and colleagues[35] also deviated from the theme of diagnosis by developing a statistical shape modeling algorithm capable of determining characteristic 3D bony features of the tibia and the femur in patients who sustained an ACL injury, which could be used for injury prediction. Ultimately, the parameters could be used to develop risk assessment tools to identify athletes who may benefit from validated ACL injury prevention programs focusing on quadriceps, hamstring, and core activation exercises, such as FIFA11+.[1] Furthermore, this technology could be used to counsel young athletes on their individual risk of ACL injury when participating in a particular sport based on their knee characteristic and could also help teams selecting athletes based on the risk analysis.

At the present time, only 1 intraoperative application of AI for knee arthroscopy has been developed. This may be explained, in part, by the difficulty of performing a study with this technology in a complex environment, such as the operating room, which requires efficient and user-friendly equipment that must be easily integrated into a sterile environment. Nevertheless, there is still a need for tools that can aid in objective intraoperative assessment. The algorithm developed by Jonmohamadi et al,[17] which was capable of identifying key anatomic features, including the ACL and menisci, is an important first step toward automated identification of complex anatomic landmarks during ACL reconstruction. For example, it has been found that the placement of tibial and femoral tunnels during ACL reconstruction is significantly different from the native anatomic footprint identified on MRI scans, suggesting that surgeons have difficulty identifying these landmarks intraoperatively.[14,34] Deep learning algorithms could potentially be trained to analyze the preoperative imaging to identify these landmarks, and this information could be merged with the arthroscopic video to suggest an optimal tunnel placement. Other intraoperative challenges that may benefit from deep learning include determining visual signs of optimal ACL graft tensioning and overconstraint of the lateral tibiofemoral joint in anterolateral ligament reconstruction. While these applications have yet to be explored, we believe that deep learning has the potential to help address some of these complex intraoperative challenges in ACL reconstruction.

Prediction of postoperative outcomes can be a valuable metric for optimizing patient care and management of patient expectations. One important postoperative consideration is pain control. A systematic review performed by Werner et al[46] demonstrated that the level of pain experienced by patients can be predicted from preoperative data. After ACL reconstruction, nerve blocks can be a useful adjunct to help patients manage their postoperative pain. However, routine use of nerve blocks for all patients is not ideal due to the potential risk of complications and prolonged rehabilitation secondary to undesired motor blockade.[24,25] Thus, a method for identifying individuals who have lower pain thresholds and may benefit from postoperative nerve blocks could be advantageous. To address this, Tighe et al[43] developed an ML classifier using only preoperative data as its input and showed promising results in the prediction of FNB, as discussed earlier. These findings may have important implications, as FNBs have been demonstrated to not only reduce postoperative pain but also to reduce opioid intake.[10] Future studies should focus on patient selection for saphenous nerve blocks, which are gaining in popularity because of their theoretical advantage in avoiding quadriceps motor blockade but may still be associated with complications, including unexpected muscle weakness.[6]

The studies highlighted in the present review also demonstrate the potential role of ML in the rehabilitation phase after ACL reconstruction. Cryotherapy, an adjunctive pain control technique that is used primarily in the setting of rehabilitation, is one potential target. By reducing tissue swelling, inflammation, and hematoma formation, it has also been shown to help improve range of motion of the knee.[11] A known limitation of this technique is the uncertainty of the inner knee temperature during the cooling period, which can vary significantly among patients. Rashkovska et al[37] proposed an ML algorithm to overcome this limitation by employing sensors placed on the skin to precisely predict the inner knee temperature. Using accurate, individualized temperature readings, the authors proposed that "smart" cooling devices could be developed to optimize patient care and expedite rehabilitation.[37]

Another important concern during rehabilitation after ACL reconstruction is the risk of reinjury, which is reported as up to 15 times higher than that for uninjured controls.[33] An important consideration in recurrent ACL tears after reconstruction is premature return to sports. Currently, there is no single objective measure that can identify athletes who have returned to their preinjury level in order to guide termination of a rehabilitation program.[39] It is now clear, however, that biomedical data, with the help of ML, can differentiate between a knee with a reconstructed ACL and a normal, uninjured knee.[39] The algorithm devised by Richter et al[39] was able to differentiate between these 2 groups, with an accuracy of >70% at up to 9 months postoperatively. The data suggested that ML algorithms could be used during the rehabilitation phase by identifying asymmetries in the biomechanics of injured knees. Physical therapists and athletic trainers could then alter training regimens to objectively target these asymmetries during the rehabilitation process to deliver tailored, sport-specific therapy.

Although ML holds much promise in the field of orthopaedic surgery, it has limitations. First, the high capital cost of ML has been identified as a potential barrier to widespread adoption in medicine.[13] The cost related to the calibration and the maintenance of the ML algorithms can also be perceived as excessive. Therefore, the overall cost of AI needs to be decreased to make this technology more accessible. Second, to train AI algorithms, large data sets are often needed. This means that important ethical considerations need to be tackled to avoid breaching patient confidentiality and consent.[8,13] Regulatory agencies would need to implement extensive precautionary measures to overcome this limitation and would need to adapt to the evolving technology. Furthermore, an inherent property of ML algorithms is their capacity to acquire knowledge, which may lead to an unexpected agency or authority in medical decision making.[8] According to Char et al,[8] this degree of autonomy would not only require stricter regulation but also may necessitate a change in how we presently conceptualize medical ethics and liability in clinical practice. Third, ML is known to exhibit a "Black Box" phenomenon, whereby little or no information is given regarding the output generated.[8,9] This limitation could lead to false discoveries, where the classifier is developed using a data set that has an incorrect association, making it of little use when applied to real cases.[9] Conversely, algorithms could also be trained to contain certain biases that may serve to favor decisions that benefit private interests instead of patients.[8] The development of algorithms capable of providing some justification for the output they generate would be of particular interest to ML applications in medicine and surgery.[3] Ultimately, to address these and other limitations presented by the adoption of ML in orthopaedic surgery, surgeons will need to work in close collaboration with data scientists to fully understand the proper way to evaluate the validity of the output provided by the algorithms and to ensure it is done in an ethical manner.

CONCLUSION

Despite the potential for AI to improve clinical practice, it has yet to deliver on those promises in a meaningful way. The ability of AI algorithms to simulate objective human thinking while constantly improving its accuracy by integrating more data can help facilitate surgical outcomes and clinical management of many injuries, such as ACL tears. Our systematic review has demonstrated that ML, a subfield of AI, is capable of aiding in the diagnosis of ACL tears, determining risk factors, and predicting the development of this injury in addition to being able to assist in the pre- and postoperative decisions for patient management. With simultaneous improvements in other related technologies, we anticipate that the current limitations may be overcome in the near future. As orthopaedic surgeons, we are poised to play a pivotal role in developing ways to practically and safely integrate this technology into our surgical and clinical workflow with the aim of improving safety, efficiency, and outcomes.

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APPENDIX

TABLE A1
Summary of Included Studies About AI in the Management of ACL Injury[a]

Lead Author (Year)	Input Feature	Goal	Type of System/AI	Primary Outcome Measure/Output	Result
			Prediction		
Pedoia[35] (2015)	Imaging: MRI	Develop 3D MRI-based statistical shape modeling and apply it in knee MRIs to extract and compare relevant shapes of the tibia and the femur in patients with and without acute ACL injuries.	From 3D MRI, a shape model was extracted for the tibia and the femur using a statistical shape modeling algorithm based on a set of matched landmarks that are computed in a fully automatic manner.	With modes of variation of all the surfaces from the mean surface (principal component analysis)	The relative distance between the condyles and the elevation of the anteromedial tibial plateau was observed to be significantly different between the injured and control groups.
Johnson[16] (2019)	Physical exam: gait analysis	Generate a machine learning algorithm capable of an on-field knee injury assessment using deep learning in lieu of laboratory-embedded force plates.	Pretrain a CaffeNet CNN model and a multivariate regression of marker-based motion capture to 3D knee-joint movement.	Compare the knee-joint movement predicted by the CaffeNet regression model with those calculated by inverse dynamics (force plate).	Of the single fine-tune investigations and the double cascade, the strongest mean knee-joint movement correlation was found for the left stance limb during sidestepping ($r = 0.9179$ and 0.9277, respectively).
			Diagnosis		
Wolf[47] (2007)	Physical exam: passive knee motion	Incorporate all 6 DOF of the knee motion and represent it as a set of instantaneous screw parameters using optical tracking, which are then used to classify knee motion.	Placement of optical trackers on both the tibia and the femur. Then, both bones were scanned using CT. The data were then analyzed using a support vector machine.	Accuracy of the SVM to identify the difference between ACL-deficient and normal knee.	For the healthy, ruptured ACL and combined ACL and PCL rupture, the accuracy was 77 ± 4.9, 83 ± 4.7, and 94 ± 1.9, respectively.
Labbe[19] (2011)	Physical exam: gait analysis	Develop a system that will objectively grade the pivot-shift test based on recorded knee joint kinematics using electromagnetic motion sensors.	The induced pivot shift was graded by the orthopaedist, and a second-degree polynomial SVM algorithm was reading the data.	Interrater agreement and accuracy of the SVM to correctly match the right pivot shift with the grade	Agreement between the subjective grades and the SVM-established grades was $\kappa = 0.83$, 0.79, and 0.82 for clinicians 1, 2, and 3, respectively.
Zarychta[48] (2015)	Imaging: MRI	Finding the feature vectors of the ACL and PCL to make it easier to diagnose them	Location and analyzation of the ACL and PCL were based on the entropy and energy measures of fuzziness and Fuzzy C-Means algorithm.	Feature vector has to include the surface area and the skeleton (B-length/A-length ratio) of the extracted structures.	Correct detection of the ACL and PCL was achieved in 89%. Differences in the surface area and the B-length/A-length ratio between healthy and injured ligaments is further described in the study.

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Table A1 (continued)

Lead Author (Year)	Input Feature	Goal	Type of System/AI	Primary Outcome Measure/Output	Result
Li[21] (2016)	Physical exam: gait analysis	Introduces machine learning algorithm into clinical diagnosis	By introducing ML, the Fuzzy C-Means clustering algorithm was used to cluster the sample set and create a set of models, and then the SVM algorithm was used to identify the new samples.	Accuracy of the SVM to identify the difference between ACL-deficient and normal knee	The final identification accuracy was 50%. In the second and third experiments, the left and right plantar pressure data were analyzed, and the accuracy was 76% and 62%, respectively.
Matić[27] (2016)	Physical exam: gait analysis	Objective test definition for unstable knee diagnosis was based on real measurements by using infrared cameras and adequate software.	A logistic regression determined the severity of the ACL injury using AP translation and IR/ER kinematics	The ACL deficiency classification was performed by applying a binary logistic regression, which also determined the significance of the AP translation and IR/ER values.	A higher exponential (Θ) for the AP translation and for the IR/ER increased the likelihood of ACL-deficient knee by 1.1758 and 2.2516 (95% CI), respectively.
Štajduhar[40] (2017)	Imaging: MRI	Evaluate a decision-support model for detecting the presence of milder ACL injuries and complete ACL ruptures from sagittal-plane MRI.	MRIs were preprocessed using a HOG or a scene spatial envelope descriptor. After classification was done, the support vector machine and random forests model classified them.	Rank the various methods in relation to their quantitative measurement of the robustness of the models learned	Experimental results suggest that a linear-kernel SVM with HOG descriptors was the best, with an AUC of 0.894 and 0.943 for the injury detection and complete rupture detection, respectively.
Bien[5] (2018)	Imaging: MRI	Assess the ability of deep learning model to detect general abnormalities and specific diagnoses (ACL tears and meniscal tears) on knee MRI exams.	MRNet, a convolutional neural network followed by a logistic regression model	The effect of providing the model's predictions to clinical experts during interpretation	Model predictions significantly increased general radiologists and orthopaedic surgeons' specificity in identifying ACL tears ($P < .001$); final sensitivity of 0.76 and specificity of 0.97.
Chang[7] (2019)	Imaging: MRI	Demonstrate the feasibility of a fully automated tool for detection of complete ACL tears.	Multiple CNN architectures were implemented.	Type of CNN algorithm with the highest accuracy	Accuracy of the 5-slice network (0.915) was better than that of the 3-slice (0.865) or single-slice (0.765). Sensitivity, specificity, PPV, and NPV of the 5-slice were 0.940, 0.890, 0.895, and 0.937, respectively.
Liu[22] (2019)	Imaging: MRI	Investigate the feasibility of using a deep learning-based approach to detect an ACL tear within the knee joint at MRI.	A fully automated deep learning-based diagnosis system was developed with 2 CNNs to isolate the ACL and detect structural abnormalities within the isolated ligament.	The sensitivity and specificity of the neural network	The sensitivity and specificity of the ACL tear detection system at the optimal threshold were 0.96 and 0.96, respectively.

(continued)

Table A1 (continued)

Lead Author (Year)	Input Feature	Goal	Type of System/AI	Primary Outcome Measure/Output	Result
Mohr[29] (2019)	EMG	Characterize abnormal muscle activity from EMG of 5 leg muscles that were recorded during treadmill walking for young adults with and without a previous knee injury.	Classification was achieved using a principal component analysis followed by a support vector machine.	Affected or unaffected leg in previously injured and previously injured vs uninjured leg	Classification rates of 83% were obtained for all patients, 100% for female patients only. It was not possible to discriminate between patterns belonging to the previously injured legs or dominant legs of controls.
Richardson[38] (2021)	Imaging: MRI	Demonstrate, using ACL tears, that a properly trained CNN can provide an acceptable surrogate for human readers when performing a protocol optimization study.	Convolutional neural network models were trained for both the FS and the matched set of NFS.	Predict the presence or absence of ACL tear in the corresponding testing sets.	AUC for NFS = 0.9983 and for FS = 0.9988. Specificity was identical (0.993) for both CNN images. FS sensitivity (0.98) and NFS sensitivity (0.88) were statistically significantly different ($P = .0253$).
Tedesco[42] (2020)	Physical exam: gait analysis	Investigate the ability of a set of inertial sensors to differentiate between healthy and post-ACL groups during a change of direction.	The different ML used in this study included k-nearest neighbors, naïve Bayes, support vector machine, gradient boosting tree, multilayer perceptron, and stacking.	Accuracy and sensitivity of different types of ML to differentiate healthy vs post-ACL injury leg	A 73.07% accuracy was obtained using the multilayer perceptron, an 81.8% sensitivity using the gradient boosting, and a 74.5% specificity using the support vector machine.
Intraoperative application					
Jonmohamadi[17] (2020)	Imaging: arthroscopy video	Automatic segmentation of multiple structures in knee arthroscopy using deep learning	Automatic segmentation of multiple structures in knee arthroscopy using deep learning	Segmented image from the arthroscope	The mean Dice similarity coefficients for femur, tibia, ACL, and meniscus were 0.78, 0.50, 0.41, and 0.43 using the U-net and 0.79, 0.50, 0.51, and 0.48 using the U-net++.
Postoperative care and rehabilitation					
Tighe[43] (2011)	Chart review	Prediction of postoperative FNB requirement after ACL reconstruction	ML classifiers based on logistic regression, BayesNet, multilayer perceptron, support vector machine, and ADTree algorithms were then developed.	The difference in prediction for FNB of simple logistic regression with other ML classifiers (BayesNet, multilayer perceptron, SVM, ADTree)	The ROC area was the greatest using the ADTree classifier (0.7), and SVM had the highest kappa value (0.242). Logistic regression outperformed other classifiers with 77.7% accuracy.

(continued)

Table A1 (continued)

Lead Author (Year)	Input Feature	Goal	Type of System/AI	Primary Outcome Measure/Output	Result
Rashkovska[37] (2015)	Predictive model	Estimate the deep temperature from the noninvasively measured data using predictive models constructed with the help of machine learning algorithm.	The ML used includes simple methods, such as linear regression and regression trees, as well as more complex methods, such as model trees.	Estimated temperature of the center of the knee (ie, in the intercondylar notch)	The model trees for scenario 2 was the best based on the small number of variables, with the correlation coefficient and the mean absolute error of 0.6541 ± 0.002117 and 1.2122 ± 0.004176, respectively.
Richter[39] (2019)	Physical exam: gait analysis	Develop and test a data-driven framework (based on no expert or prior knowledge) to classify movement patterns of normal and rehabilitating athletes using only biomechanical data.	Motion analysis using 8 cameras synchronized with 2 force platforms. Identification of the best machine learning and the best exercise was performed.	Classify movement data into normal, operated ACL tear (ACL_{OP}), and contralateral leg of ACL tear (ACL_{NoOP}) without expert knowledge.	The best exercise was the double-leg drop jump, with an accuracy of 81% and when considering only for the ACL_{OP} and ACL_{NoOP} class (84%). All were done using the neural network.
Anderson[2] (2020)	Chart review	Build a cross-validated model that predicts risk of prolonged opioid use after a specific orthopaedic procedure (ACL reconstruction).	Logistic regression, random forest, Bayesian belief network, and gradient boosting machine models	Likelihood of prolonged opioid use, defined as any opioid prescription filled > 90 d after ACL reconstruction	Gradient boosting machine: the final model is accurate, with a Brier score of 0.10 (95% CI, 0.09-0.11) and the AUC of 0.77 (95% CI, 0.75-0.80)

[a]ACL, anterior cruciate ligament; ADTree, alternating decision tree; AI, artificial intelligence; AUC, area under the curve; AP, anteroposterior; CT, computed tomography; CNN, convolutional neural network; DOF, degree of freedom; EMG, electromyography; exam, examination; FS, fat-saturated; FNB, femoral nerve block; HOG, histogram of oriented gradients; IR/ER, internal/external rotation; ML, machine learning; MRI, magnetic resonance imaging; MRNet, a convolutional neural network for classifying MRI series and combined predictions from 3 series per exam using logistic regression; NFS, non–fat saturated; NoOP, non-operated knee, contralateral to the operated limb; NPV, negative predictive value; OP, operated limb; PCL, posterior cruciate ligament; PPV, positive predictive value; ROC, receiver operating characteristic; SVM, support vector machine; 3D, 3-dimensional.