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Artificial Intelligence in ACL Injury Diagnosis and Physical Therapy Rehabilitation

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Abstract. Diagnosis of an ACL injury is followed by a personalized rehabilitation program and subsequent decisions regarding sport resumption. AI algorithms may be used in assessing such patients and readiness for sports participation using imaging and biomechanical parameters. This review summarizes the current status of AI-supported ACL diagnosis via clinical examination and MRI, rehabilitation and return-to-sport assessment. Using wearable sensors with machine learning, clinicians can quantify movement during the clinical examination of knee joint. Furthermore, deep-learning models showed promise in detection of ACL tears via MRI imaging. During the rehabilitation process, AI can help quantify movement-related load, detect strength asymmetries and predict functional recovery afterwards. Return-to-sport models can integrate physical and psychologic patient's data to predict readiness to resume training and the risk of re-injury. Nevertheless, all these applications answer different clinical questions and good performance in research datasets does not ensure the effectiveness of these tools in clinical practice. The limitations in the patient populations, measurement approaches and definitions of outcome, as well as a lack of external validation, decrease the generalizability of results. Thus, AI models should give clear and verifiable information which clinicians can apply in clinical practice.

Keywords: Anterior cruciate ligament (ACL), artificial intelligence, injury diagnosis, physical therapy rehabilitation, return to sport

1. Introduction

One of the biggest stabilising structures in the knee joint is the anterior cruciate ligament or ACL. The ACL restricts translation of tibia anteriorly to femur and helps to stabilize tibia during rotational movements. The ACL consequently plays a significant role in sports that require rapid deceleration, jumping, landing, cutting and pivoting. ACL injuries are very important injuries for athletes, and there is variation in the incidence of these injuries based on sport, sex, and level of play. Systematic review of systematic reviews recently revealed that in sports like American football, basketball, soccer, and volleyball, the incidence of ACL injuries is relatively high, and that in some similar sports, there were higher incidences of ACL injuries among female athletes [1]. A meta-analysis of 89 studies also showed that there was significant heterogeneity in risk of developing an ACL injury between sex, sport, and competition level and not one single percentage that provides a true reflection of the risk of an ACL injury [2].

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The diagnosis and treatment of an ACL injury is more than just determining if the ACL is torn. Decisions by clinicians need to be made as to the severity of the injury, associated knee injury, functional restriction, and patient's goals. If patients have ACL reconstruction (ACLR), patients cannot use the knee normally after surgery. Physical therapy will be required to restore ROM, muscle strength, balance, neuromuscular control, movement quality and confidence. Evidence-based guidelines are increasingly advocating criterion rather than purely time based progression as there is significant variation in recovery between patients [3, 4].

Artificial intelligence (AI) could offer extra weapons to deal with a number of the challenges during this journey. The term "AI" is an umbrella term for computer systems that are able to do things like pattern recognition, classification, and prediction. Machine learning enables the computer model to recognize relationships among data, and deep learning via multi-layered neural networks is especially effective when dealing with complex medical data or data that records movement. This paper highlights three areas: AI-assisted diagnosis of ACL using sensor-based clinical assessment and interpretation of MRI, AI-assisted monitoring during physical therapy, and machine-learning-assisted return to sport decision making. In each of the applications, AI is meant to supplement the clinician making the final decision and give them extra objective data that can aid in clinical reasoning and individual patient care.

2. AI for ACL injury diagnosis

2.1. Clinical examination and sensor assistance

Evaluation of a suspected ACL injury typically starts with an evaluation of the mechanism of injury and the patient's symptoms. Patients can experience a 'pop' at the time of injury, swelling, pain and knee instability. Such symptoms give good clues to an ACL injury, especially when symptoms are experienced during landing, pivoting, and/or changes of direction. A physical exam typically includes the Lachman and pivot-shift tests to assess knee instability [5]. The anterior drawer test is also used in clinical assessment [6]. History and physical exam combine to form a clinical suspicion, which helps to determine further imaging and treatment.

However, some problems prevent the use of these tests. Immediate pain and swelling after an injury will make it hard to examine because of protective muscle guarding. However, interpretation of the diagnosis may also be influenced by the examiner's level of experience and the examiner's ability to detect fine movements. Recent research has therefore been carried out on how to measure the physical exam.

Allott et al evaluated wearable inertial measurement unit (IMU) sensors in 50 people during the Lachman and anterior drawer tests [6]. The sensors measured linear acceleration in all three axes and angular velocity and the data of the injured leg were compared with the contralateral leg with a neural-network model. Comparative-leg model obtained a diagnostic accuracy of 81% for the subjects at the subject-wise level. Based on these results, the model could be used in conjunction with measurements provided by the sensors, but the small feasibility study does not show that measurements provided by the sensor could replace the clinical examination.

2.2. MRI assessment and deep learning

Clinical tests and measurements from the sensors may be able to detect abnormal knee movements, but these evaluations cannot actually visualize the damaged tissues. Magnetic resonance imaging (MRI) is used to get a closer look at the ACL injury when the history and physical exam indicate

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this. MRI provides the ability for doctors to not only view the ACL, but also the surrounding menisci, cartilage, bones and other knee ligaments. It is relevant to have this wider perspective as some cases of ACL tears can be accompanied by other intra-articular injuries that will impact treatment and rehabilitation. While MRI is very descriptive, there can still be difficulties in its interpretation. Partial ACL tears are not always as easy to diagnose as complete tears and may require more skill on the part of the interpreter. Additional uncertainty can occur due to differences in image quality, MRI sequences and scanning protocols [5]. Given these challenges, recent studies have started to investigate deep learning as a tool to support MRI interpretation. An AI system can be trained to find the ACL, recognise imaging patterns indicative of a tear and offer a second result to the radiologist's consideration.

In a review by Mercurio et al. 23 studies were analyzed that used deep-learning techniques for ACL injury detection on MRI. Many of the algorithms exhibited high diagnostic performance, and potential to enhance the efficiency and consistency of image interpretation [5]. The review also highlighted that excellent results with research datasets do not necessarily signify that a model is ready to be used in the clinic routinely. Data quality, MRI protocol variations, and validation procedures are some of the factors that still need to be resolved before the systems could be used with confidence in other hospitals and patient populations.

An example of how these systems work is given by Alic et al. [7]. They analysed 8,086 sagittal knee MRI slices, with the patient's ACL status verified by arthroscopy. Two stages in the system were used: a first stage to model the localization of the ACL region using a model and a second stage to classify if the tear was present or not, using a customized deep-learning model. The authors reported 91.5% accuracy and 92.4% sensitivity. Both complete and partial ACL tears were included in the dataset. However, the paper reports 253 patients while its listed training, tuning, and validation groups total 252, and its descriptions of the data split are inconsistent. These reporting issues limit confidence in the performance estimates. The findings should therefore be treated as preliminary and independently validated across institutions before clinical use.

At the larger scale, results of meta-analyses suggest that the optimistic results do not pertain to one algorithm. Gill et al. reviewed 36 studies that included 52 AI models for detecting ACL tears on MRI [8]. Pooled accuracy, sensitivity and specificity were respectively, 87.37%, 90.73% and 91.34%. Pooled sensitivity of Moraes de Oliveira et al. was about 94% and pooled specificity was about 93% [9]. Overall, there was no significant difference between AI systems and radiologists in terms of diagnostic accuracy. Overall, these reviews indicate that AI can accurately detect ACL tears with a high performance. But there is the issue of the variation between individual models, study designs, imaging protocols, and patient samples in the pooled estimates. The most plausible conclusion is thus that AI can assist in diagnosis using MRI, rather than that all systems are equally successful in all environments.

The clinical usefulness of these systems is based on how these systems enhance the diagnostic process. A model could indicate potential areas of concern, bring attention to a subtle area or offer a consistent second read. However, the clinician would still have to take into account the patient's history and physical examination, quality of the images, other injuries, and treatment objectives. This approach combines AI's swift pattern recognition with the healthcare worker's expert judgment and accountability. This combination may prove particularly helpful in cases that are less clear using imaging alone, or if a partial tear is not easily differentiated.

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3. AI in rehabilitation and return to sport

Machine learning is being studied for both rehabilitation monitoring and return-to-sport decisions, but these applications address different stages of recovery. Kumar et al. reviewed 40 studies involving machine-learning applications in ACL injury prediction, rehabilitation monitoring, and return-to-sport assessment [10]. Models such as random forest and extreme gradient boosting were frequently used to analyze clinical, biomechanical, and wearable-sensor data. The review concluded that machine learning has strong potential as a decision-support tool, particularly because machine learning can integrate information collected from different parts of the rehabilitation process. However, external validation and standardized outcome definitions were inconsistently reported, complicating efforts to determine whether the results will remain accurate in new patient groups.

3.1. Monitoring rehabilitation progress

During rehabilitation, the immediate purpose of assessment is to determine how the patient is recovering and which impairments need treatment. Physical therapists monitor symptoms, range of motion, muscle strength, balance, and movement quality to guide exercise progression [3, 4]. AI can support this process by analyzing repeated measurements and identifying deficits that may be difficult to recognize from a single score. This use of AI concerns the adjustment of ongoing treatment; deciding whether an athlete is ready for unrestricted competition requires additional assessment later in recovery.

Chen et al. examined a direct application to rehabilitation monitoring in 25 patients after ACL reconstruction [11]. The researchers combined wearable-sensor data with deep learning to estimate vertical ground reaction force during walking, running, and stair descent. This force describes the vertical force exerted by the ground on the body and provides information about movement-related loading. The best model achieved coefficients of determination of 0.953 for walking, 0.971 for running, and 0.979 for stair descent. These findings suggest that wearable measurements may help extend loading assessment beyond laboratory force plates. For physical therapists, this could provide information about how patients load the limb during everyday tasks. However, accurate force estimation in a small study does not establish that using the system improves recovery, and performance needs confirmation in other patient groups.

Machine learning may also reveal strength deficits that are obscured by summary scores. Nolte et al. analyzed isokinetic knee-test data from 366 male and 183 female athletes, including 63 males and 72 females after ACL reconstruction [12]. Random forest models distinguished athletes after reconstruction from healthy controls, with areas under the receiver operating characteristic curve (AUCs) of 0.90 and 0.92 for males and females, respectively. Measures involving the affected leg and between-leg differences were influential, particularly eccentric hamstring work. This supports examining detailed strength patterns when identifying rehabilitation needs. The models classified group differences, however; the models did not demonstrate that a particular exercise prescription improves outcomes or that an individual athlete is ready to return to sport.

Alongside the assessment of current impairments, machine learning may help predict later recovery from measurements obtained early in rehabilitation. Hwang et al., for example, used physical-performance data collected three months after surgery from 113 patients to predict subjective knee function, symptoms, and psychological readiness 12 months after ACL reconstruction [13]. The findings suggest that information gathered early in rehabilitation may help clinicians identify whether a patient is progressing as expected or may need additional intervention.

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This type of prediction would not determine return-to-sport clearance alone, but the prediction could alert the physical therapist to problems that might otherwise become apparent only later in recovery.

This individualized information can help physical therapists identify treatment priorities during rehabilitation. For example, an athlete may reach 90% limb symmetry on a strength measure and perform successfully on a hop test, suggesting progress. However, the same athlete may still demonstrate poor balance, altered landing mechanics, reduced confidence, persistent symptoms, or insufficient quadriceps strength. A machine-learning model could combine these measurements and help the clinician see that the overall recovery remains incomplete. The physical therapist could then verify the model's findings through clinical examination and focus treatment on the specific weaknesses instead of relying only on a general return-to-sport score. In this way, the model supports a more individualized rehabilitation plan rather than substituting for the therapist's assessment.

3.2. Assessing return to sport readiness

To make decisions about returning to sport, athletes must be evaluated to determine their readiness.

In the latter stages of rehabilitation the focus moves away from addressing impairments and onto whether or not the athlete can perform in sport. Return to sport readiness is hard to determine and one measurement does not accurately convey readiness. Wright et al. examined 33 studies with over 6,000 participants and identified significant differences in the type and criteria used to make the decision to return to sport [14]. Strength and hop performance were commonly used, with a limb symmetry index (LSI) of 90% or greater frequently used. Biomechanics, agility, change of direction, movement quality and other sport specific skills were however, less consistently assessed. Van Haren et al. also found jump performance, muscle strength, physical function and psychological readiness to return to sport as factors associated with return to sport [15]. The authors judged the certainty of the evidence as very low, indicating the challenges of predicting a successful return using traditional measures. The inconsistencies also pose problems for physical therapists, who will need to track progress during the course of the rehabilitation, and determine what deficits are clinically significant.

Another important aspect in deciding when the athlete is ready to return to sport is psychological recovery. A systematic review and network meta-analysis were performed by Lo et al. to assess physical, psychological and subjective return-to-sport assessments [16]. The results suggest that physical and mental readiness should be considered as a combined assessment instead of an outcome in itself. Athletes can return to strength and balance and still have decreased confidence or fear of reinjury and a decrease in the ability to perform the hop. These limitations may not be apparent on a short term physical assessment but can impact on how the athlete moves and reacts in competition. Machine learning can be useful as machine learning can analyze the relationships between multiple variables simultaneously. Quadriceps strength, balance, hop-test results, symptoms, mental readiness, and self-reported function can all be considered as part of a model that assesses the overall pattern of recovery, and which can determine which factors are still limiting the athlete.

Time to sport is another important factor. Reinjury rates were found to be significantly reduced with delayed return to Level I sport, especially in the first 9 months following ACL reconstruction [17]. Beischer et al. reported that, among athletes aged 15–30 years, returning to knee-strenuous sport before 9 months after ACL reconstruction was associated with a higher rate of second ACL injury than returning at 9 months or later (hazard ratio, 6.7; 95% confidence interval, 2.6–16.7) [18]. These findings do not determine whether an individual athlete is ready to return. Rather, these

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findings indicate that the time for return needs to be evaluated in conjunction with physical recovery, movement quality, symptoms, and psychological readiness. This manual process of recording and integrating all measurements made during repeated rehabilitation visits can be challenging for clinicians. A well-validated model might structure the information and provide patterns without making the final decision an automatic or purely statistical decision.

Using these measurements together in a prediction model could aid in determining risk of future ACL injuries. Greenberg et al. created a model for young athletes following ACL reconstruction, which comprised 33 variables, 23 of which were modifiable. In the holdout dataset, the model had a reported sensitivity of 94.3% and specificity of 71.5% [19]. Athletes classified as high risk had 4.5 times the odds of sustaining another ACL injury compared with those classified as low risk. The holdout data came from the same institution, so external validation remains necessary. One aspect that proved especially useful was that the system wasn't simply high-risk or low-risk. The system was also able to determine the factors that were most important for each individual in the classification. This makes the output more clinically relevant as modifiable factors such as strength or movement deficits can be specific targets for ongoing rehabilitation.

There is less convincing evidence across the wider evidence base. Ahmed et al conducted a review of 10 studies that used AI to predict a reinjury or adverse event following ACL reconstruction. Different outcomes, data sources and modeling approaches were used in the studies [20]. Most used internal validation, with external validation being less frequently reported and reporting of calibration and clinical utility being inconsistent. These results reduce the confidence in a model to give good risk estimates for athletes not included in the original data set. Predictions should therefore only be considered as exploratory and should be verified from the examination and recovery history of the athlete.

3.3. Using evidence to inform clinical decisions

Overall, these uses demonstrate the potential for AI to aid in the ongoing treatment and subsequent return to sport within the same rehabilitation pathway. The most valuable asset is the capacity to integrate physical, functional, biomechanical, psychological and patient-reported data, which are frequently spread out across various tests and visits. The output should be viewed as a risk profile and not necessarily as a clearance. However, it is still the clinicians' responsibility to verify the validity of the data and to assess if the identified factors are appropriate for the patient's clinical presentation, as well as to understand the sport specific demands and personal goals of the patient and to decide which factors require additional treatment. AI used in this way can render decisions about rehabilitation and return to sport more transparent, objective and individualized.

4. Limitation and prospects for the future

While AI holds promise for enhancing treatment and rehabilitation in ACL, there are several factors that can hamper the complete incorporation of AI. One of the main issues is the quality and continuity of the data which is used to train the models. The various MRI machines, rehab programs, test methods and data recording systems can differ between hospitals and physical therapy clinics. There is also a possibility of differences in patient populations in terms of age, sex, sport, competition level, and access to care. Thus, a model that works great in one environment may not work so well in another. Gill et al. highlighted significant variations between AI models, MRI protocols and study designs; and Kumar et al. noted that external validation was not consistent across machine-learning studies for ACL rehabilitation and return to sport assessment [8, 10].

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One challenge is that some AI models are not easily comprehensible for clinicians. A model can be made to predict that the athlete is at a high risk of reinjury, or that the athlete isn't ready to return to sport, but the model will not explicitly explain why. A risk score is not sufficient for physical therapists. It is important for clinicians to be aware of the factors that may have influenced the outcome, such as muscle weakness, movement asymmetry, decreased balance, symptoms, and psychological readiness. This information is crucial to consider when determining if the prediction is clinically reasonable and the treatment response to select. This has led to a recent focus on building more transparent and explainable AI models prior to their adoption in the clinical setting [10].

Issues of practicality and ethics need to be taken into account as well. The cost of advanced sensors, software, and AI systems may be prohibitive, and they might not be available in all rehabilitation settings. Doctors must be educated to accurately gather data, identify erroneous results and incorporate data into their current workflow. Patient medical, imaging, psychological and movement data also needs to be stored and protected in an appropriate manner. Moreover, an algorithm developed based on a small number of patients may yield less accurate results for groups of patients for which there was insufficient representation during algorithm development. AI powered reinjury prediction models are still largely exploratory due to a number of studies having limited external validation and varying definitions of outcomes [20].

Thus, future studies should be addressed to improve the accuracy of the models as well as to render the systems interpretable, inexpensive, safe and usable by the clinicians. Additional multicenter studies of various patient groups, sports, MRI procedures, and rehabilitation conditions are required. The performance of models in new settings, which variables affect each prediction and whether errors occur differently for certain patient groups should be reported to researchers. Most significantly, future research is required to determine if implementation of AI alters treatment decisions, enhances function, decreases reinjury rates and assists with safe return to sport. While it is important to have high accuracy in predicting, it is more significant to improve the clinical value of information if it can be used to improve care.

5. Conclusion

Artificial intelligence has shown growing potential across different stages of ACL injury management. In diagnosis, deep-learning models can assist with MRI interpretation and have demonstrated diagnostic performance comparable to radiologists in recent studies. Wearable sensors can make subtle knee motion more measurable during clinical testing. During rehabilitation, models can also help assess movement-related loading and strength deficits, providing physical therapists with information for treatment planning. Machine-learning models may also help clinicians combine physical, functional, biomechanical, and psychological information when evaluating readiness to return to sport and the risk of another injury.

However, the evidence does not support using AI as a replacement for physicians, radiologists, or physical therapists. ACL injury and recovery involve measurable physical data as well as symptoms, movement quality, confidence, patient goals, and sport-specific demands. Model performance may also change when the system is used with a new population, scanner, rehabilitation protocol, or testing method. For these reasons, clinicians must evaluate whether an AI result is consistent with the patient's full presentation and understand which factors influenced the prediction. AI is most useful when AI organizes complex information, highlights possible concerns, and supports a decision that remains grounded in clinical judgment.

Looking ahead, a useful direction is to connect these applications across the course of recovery. Future systems could bring imaging findings, repeated movement and strength measurements, and

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patient-reported outcomes into a shared record that helps clinicians recognize changes over time. Developing such systems will require collaboration among researchers, physical therapists, physicians, and patients, with prospective testing across different clinical settings. The value should be judged by whether the systems improve treatment decisions, patient function, and the safety of return to sport. With explainable outputs and stronger evidence of clinical benefit, AI may become a practical part of individualized ACL care while clinicians retain responsibility for the final decision.

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