Current Pain and Headache Reports (2024) 28:229–238
https://doi.org/10.1007/s11916-024-01224-8

Applications of Artificial Intelligence in Pain Medicine

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Accepted: 30 January 2024 / Published online: 12 February 2024

Abstract

Purpose of Review This review explores the current applications of artificial intelligence (AI) in the field of pain medicine with a focus on machine learning.

Recent Findings Utilizing a literature search conducted through the PubMed database, several current trends were identified, including the use of AI as a tool for diagnostics, predicting pain progression, predicting treatment response, and performance of therapy and pain management. Results of these studies show promise for the improvement of patient outcomes.

Summary Current gaps in the research and subsequent directions for future study involve AI in optimizing and improving nerve stimulation and more thoroughly predicting patients' responses to treatment.

Keywords Artificial intelligence · Pain medicine · Machine learning · Chronic pain

Introduction

In its most general form, artificial intelligence (AI) is often thought of as machines emulating human cognition. More practically, AI is a broad field that represents technologies capable of reasoning and performing tasks such as classification, problem-solving, decision-making, and forecasting future states [1]. Within the rapidly expanding field of AI, this review focuses on machine learning and deep learning, two of the most widely referenced forms of AI today. Both terms represent their own subfields within the broader scope of artificial intelligence and are subjects of extensive research.

The subfield of machine learning, specifically, focuses on developing algorithms that can recognize patterns in data and then apply those patterns to improve at given tasks [2]. A key feature of machine learning is that algorithms improve through exposure to more data without the need for intervention or explicit programming [1]. Machine learning itself comprises several subcategories, each with distinct approaches to problem-solving.

Supervised learning is one such approach in which models are trained to classify new data into predefined categories (i.e., distinguishing between images of cats and dogs) using labeled datasets [3]. In contrast, unsupervised learning does not involve predefined categories, rather, data is given to the algorithm without labels to find new patterns or discrete categories (i.e., clustering) [2].

Reinforcement learning is a method in which algorithms learn through trial and error [1]. For instance, an algorithm might learn to play a game by receiving "rewards" for making good moves and "penalties" for making bad moves. Lastly, an advanced form of machine learning known as deep learning involves the use of complex algorithms to create multi-layer artificial neural networks. These artificial neural networks consist of layers of nodes in which each node is connected to every other node in the neighboring layers [4]. While networks consist of varying numbers of layers and nodes, each network contains an input layer where data enters the network, at least one hidden layer that transforms the input, and an output layer that provides the result [4]. The network mimics the nervous system where nodes represent neurons in that they receive a weighted input and proceed to activate nodes further along in the network resulting in complex activation pathways [1]. Artificial neural networks

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are adept at performing complex tasks ranging from pattern recognition to data analysis [5].

Methods

A literature search was conducted through the PubMed database using various combinations of the words, "Artificial Intelligence," "Pain Medicine," "Machine Learning," and "Chronic Pain." To be included, studies were required to have investigated an application of AI within the field of pain medicine. Studies related to anesthesiology, including preoperative, intraoperative, and post operative care were excluded to maintain a scope focused on long-term pain management. Narrative and systematic reviews were also excluded to ensure the inclusion of primary research. No selection criteria were made on the publication date.

Current Applications of AI in Pain Medicine

A. Diagnostic Aid

Study	Objective	Design	Sample size and population	AI technology used	Key findings
Abdollahi et al. [6]: "Using a motion sensor to categorize nonspecific low back pain patients: a machine learning approach"	Create a kinematic sensor-based machine learning (ML) model that can classify non-specific lower back pain (NSLBP) patients into risk groups.	Observational study using inertial measurement units (IMUs) for kinematic data and STarT back screening tool results as objective truth.	94 patients with NSLBP.	Support vector machine (SVM) and multi-layer perceptron (MLP).	Kinematic data can be used to classify patients as high vs. low risk with 75% accuracy (SVM) and 60% accuracy (MLP).
Staartjes et al. [7]: "Initial classification of low back and leg pain based on objective functional testing: a pilot study of machine learning applied to diagnostics"	Determine the efficacy of the Five Repetition Sit to Stand Test (5R-STS) as a diagnostic tool in patients with low back pain.	Prospective study.	292 patients.	Fuzzy rule-based system.	High accuracy (~96%) when using 5R-STS results with ML to classify patients as having lumbar disk herniation, lumbar spinal stenosis, or NSLBP.
Gruss et al. [8]: "Pain intensity recognition rates via biopotential feature patterns with support vector machines"	Create a ML pain recognition system that can objectively categorize pain levels based on biopotential data.	Experimental study subjecting participants to controlled levels of painful heat stimuli.	85 participants.	SVM.	The ML model achieved high classification rates using biopotential data (~91% for baseline vs. pain tolerance threshold; ~79% for baseline vs. pain threshold).
Liew et al. [9]: "Interpretable machine learning models for classifying low back pain status using functional physiological variables"	To evaluate the use of ML models in classifying healthy controls and low back pain (LBP) subgroups using kinematic and electromyographic data.	Observational study using motion capture with electromyography assessments on participants during lifting exercises.	49 participants (healthy control = 16, low back pain remission = 16, and current low back pain = 17).	Functional data boosting.	High accuracy when classifying LBP status directly: AUC of 90.4% for model trained on control vs. current LBP, 91.2% for control vs. LBP in remission, and 96.7% for LBP in remission vs current LBP.
Lee et al. [10]: "Machine learning-based prediction of clinical pain using multimodal neuroimaging and autonomic metrics"	Develop machine learning models to objectively classify a patient's pain level using neuroimaging and heart rate metrics.	Experimental study subjecting patients to pain exacerbating maneuvers.	53 patients with chronic lower back pain.	SVM, SVR.	Classification of pain levels within individual patients saw an accuracy = 92.45%, and area under the curve = 0.97. When creating a regression to predict pain in new patients, the prediction was significant (r = 0.63).

*A sample of studies on applications of AI as a diagnostic aid.

Several studies were identified that utilized AI as a diagnostic aid. These studies ranged from determining the cause of chronic pain to determining chronic pain risk and severity. One study by Staartjes et al. [7] looked at applying AI to the time it took patients to complete a functional impairment test (five times sit-to-stand test) to help in diagnosing the cause of back pain. Researchers in the study trained a machine learning algorithm to classify patients as having either lumbar disk herniation, lumbar spinal stenosis, or chronic lower back pain based on the time demographic data and the time it took a patient to complete the test. The algorithm was able to correctly identify a patient's condition with ~ 96% accuracy.

In addition to identifying the cause of chronic pain, two studies were reviewed that used machine learning for stratifying patients by chronic pain risk. Abdollahi et al. [6] studied the use of wearable kinematic sensors in categorizing nonspecific lower back pain. The researchers had participants perform a range of movements wearing kinematic sensors and then used different machine-learning approaches to categorize the patients into risk groups based on previously collected kinematic data. Using the STarT back screening questionnaire as the source of truth, the neural network model was able to categorize high risk vs. low-medium risk with ~ 60% accuracy while the supervised learning algorithm categorized patients with ~ 75% accuracy.

Lastly, a common goal across several studies was to use machine learning to develop an objective measure of a patient's pain severity. Different studies approached this problem in unique ways. Gruss et al. [8] looked at the use of biopotential data to categorize different pain levels. Researchers collected biopotential data on participants while exposing them to painful heat stimuli. The researchers labeled the data with various thresholds of pain including a baseline, where the participant first felt pain, and the maximum pain tolerance. Using a machine learning algorithm, they were able to optimize a pain recognition system that could distinguish between the baseline pain level and the maximum pain tolerance level with 90.94% accuracy. Alternatively, other studies such as Wu et al. [11•] looked to train systems to identify pain based on images or videos of patients.

B. Modeling Pain Progression

Study	Objective	Design	Sample size and population	AI technology used	Key findings
Guan et al. [12••]: "Deep learning approach to predict pain progression in knee osteoarthritis"	To develop and evaluate deep learning models with the purpose of predicting if pain would worsen or improve in patients with or at risk for knee osteoarthritis.	Retrospective analysis.	9348 knees from 4674 subjects with or at risk for knee osteoarthrosis.	Artificial neural network.	Deep learning models trained with knee radiographs had better diagnostic performance (AUC of 0.807 and 0.77) than traditional models that use solely demographic, clinical, and radiographic risk factors (AUC of 0.69).
Liu et al. [13]: "Predictive models for knee pain in middle-aged and elderly individuals based on machine learning methods"	Utilize machine learning to develop a model that can predict knee pain in middle aged and elderly individuals.	Retrospective analysis.	5386 individuals above the age of 45.	Logistic regression, random forest, and extreme data boosting.	Logistic regression showed the greatest accuracy in predicting knee pain with an AUC of 0.71.
Lin et al. [14••]: "Prediction of knee pain improvement over two years for knee osteoarthritis using a dynamic nomogram based on MRI-derived radiomics: a proof-of-concept study"	Create and test a nomogram that uses MRI scans and patient characteristics to predict improvement in knee osteoarthritis.	Proof of concept study.	216 patients with knee osteoarthritis.	Least absolute shrinkage and selection operator regression for feature selection and multivariate logistic regression for creation of the nomogram.	The nomogram showed good performance in the training and test set (AUC of 0.79 and 0.83) for predicting a 20% improvement in pain symptoms over 2 years.

Study	Objective	Design	Sample size and population	AI technology used	Key findings
Goldstein et al. [15]: "Emerging clinical technology: application of machine learning to chronic pain assessments based on emotional body maps"	Use a mobile platform that gathers data on pain and emotional states in patients with chronic back pain to create a model for predicting future pain.	Observational study, in which, the final model is used to predict high or low pain level (given by a numeric threshold) 2 weeks into the future.	65 chronic back pain patients.	Linear regression with leave-one-participant-out cross-validation.	The predictive accuracies were 65% and 72% with respect to the two models created.

*A sample of studies on applications of AI in modeling pain progression.

Another common application of AI in pain medicine is for predicting the progression of chronic pain. Of the articles reviewed, four examined the use of AI as a predictor of pain. One representative study by Guan et al. [12••] sought to examine the potential for AI to assess the risk of chronic knee pain progression in patients who have or are at risk of developing knee osteoarthritis. In doing so, the researchers trained three artificial neural networks (ANN) to identify if a patient's knee pain would worsen over 48 months using a dataset of 4200 knees containing patients with and without chronic knee pain progression. The first ANN was trained using only traditional risk factors (demographic, clinical, radiographic), the second was trained using only baseline knee radiographs, and the third was trained using a combination of the baseline knee radiographs and traditional risk factors. The first model was able to correctly predict worsening pain ~ 69% of the time, the second was correct ~ 77% of the time, and the third was correct ~ 81% of the time. In a similar manner, researchers Lin et al. [14••] employed machine learning techniques to create a tool that could predict improvements in arthritic patients' knee pain using features extracted from MRIs. The model they created correctly predicted pain improvement in 83% of test cases. The results from Guan et al. [12••] and Lin et al. [14••] primarily illustrate the feasibility of AI in effectively modeling pain progression. Further, the study by Guan et al. [12••] is a prime example of how AI can be leveraged to interpret complex qualitative data directly, such as a knee radiograph.

C. Predicting Patient Treatment Response

Study	Objective	Design	Sample size and population	AI technology used	Key findings
Ichesco et al. [16]: "Prediction of differential pharmacologic response in chronic pain using functional neuroimaging biomarkers and a support vector machine algorithm: an exploratory study"	Use baseline brain connectivity patterns to predict if patients with fibromyalgia would respond differently to pregabalin or milnacipran.	Double-blind, placebo-controlled crossover study.	28 patients with fibromyalgia.	SVM.	Posterior cingulate cortex and dorsolateral prefrontal cortex connectivity patterns could together predict pregabalin vs milnacipran responders with 92% accuracy.
Verma et al. [17]: "Exploratory application of machine learning methods on patient reported data in the development of supervised models for predicting outcomes"	Investigate the ability of different machine learning methods to predict outcomes in patients with low back and/or non-specific neck pain.	Retrospective analysis.	Two previous studies were used. Study 1 $n = 377$ and study 2 $n = 1040$.	Seven regression algorithms and 2 classifier algorithms.	Regression methods performed well in predicting patient reported outcomes such as pain and ability to work. Classifier methods performed poorly when predicting a patient's referral for treatment.
Tu et al. [18]: "Multivariate resting-state functional connectivity predicts responses to real and sham acupuncture treatment in chronic low back pain"	Determine if ML approaches using functional MRI scans can predict a patient's response to real or sham acupuncture.	Randomized single blind trial.	50 chronic lower back pain patients.	Support vector regression.	Pretreatment resting state functional connectivity patterns could predict changes in pain with a coefficient of determination of 34% and 29% for real and sham acupuncture.

Study	Objective	Design	Sample size and population	AI technology used	Key findings
Branco et al. [19]: "Predicting placebo analgesia in patients with chronic pain using natural language processing: a preliminary validation study"	Evaluate if the way a patient talks about their life can predict if they will experience a placebo response.	Retrospective validation study. Two studies were analyzed, one where patients were given a placebo and another where they were given either a placebo or treatment.	116 individuals.	Natural language processing to extract language features. Bidirectional stepwise logistic regression for prediction.	The model showed accuracy in using patient interviews to predict who would respond to a placebo (AUC of 0.71). Patients predicted as placebo responders experienced an average 30% reduction in pain from an inert pill, compared to 3% for non-responders.

*A sample of studies on applications of AI in predicting patient treatment response.

Four articles were reviewed that involved the use of AI for predicting how patients will respond to different treatments. The study by Ichesco et al. [16] illustrates a representative use case with broad applications. Researchers in the study attempted to create a supervised learning model to predict how patients with chronic pain due to fibromyalgia would respond differently to two drugs. The model was trained to classify patients as being responders ($\geq$ 20% reduction in pain) to either pregabalin or milnacipran. The dataset used to train the model consisted of resting state MRI scans of the brain looking at connectivity patterns between the posterior cingulate cortex and dorsolateral prefrontal cortex. The results of the study show that the connectivity patterns found in the MRI were able to classify if a patient would be a pregabalin or milnacipran responder with 92% accuracy.

While the study showed promising results in assessing differential drug responses, it could not predict if a patient would respond to the drug directly. One study that examined if a patient would experience a specific response was conducted by Branco et al. [19] Researchers sought to determine if a patient's rhetoric could predict if they would experience a placebo effect. In doing so, the researchers developed a machine learning model trained on patient interviews and their corresponding responses to placebo medication. When tested, the model was able to correctly predict if a patient would have a placebo response in 71% of the test cases using the language patients use to talk about their pain and life.

Improving Treatment and Pain Maintenance

Study	Objective	Design	Sample size and population	AI technology used	Key findings
Ortiz-Catalan et al. [20]: "Phantom motor execution facilitated by machine learning and augmented reality as treatment for phantom limb pain: a single group, clinical trial in patients with chronic intractable phantom limb pain"	Evaluate if the use of augmented reality and machine learning to allow patients with phantom limb pain (PLP) to control a virtual limb can lead to a reduction in PLP.	Experimental study in which intended phantom limb movements are determined using ML. These movements are then shown on a screen for a patient to see in real time.	14 patients with chronic PLP.	Myoelectric pattern recognition.	Significant improvement was seen in PLP metrics between the first and last session (47% reduction in weighted pain distribution, 32% in numeric rating scale, and 51% in pain rating index)
Piette et al. [21]: "Patient-centered pain care using artificial intelligence and mobile health tools"	Can a ML model personalize a patients cognitive behavior therapy for chronic pain (CBT-CP) treatment for non-inferior outcomes and less therapist time.	Randomized, noninferiority, comparative effectiveness trial.	278 patients with chronic back pain.	Reinforcement learning.	Using daily patient pain updates, a ML model was able to selectively suggest shorter CBT-CP session durations with noninferior outcomes to 45-min sessions and less than half the therapist time.

Study	Objective	Design	Sample size and population	AI technology used	Key findings
Marcuzzi et al. [22]: "Effect of an artificial intelligence-based self-management app on musculoskeletal health in patients with neck and/or low back pain referred to specialist care: a randomized clinical trial"	Evaluate how the efficacy of an AI based app for personalized chronic pain management advice compares to traditional methods.	Randomized clinical trial.	294 adults with neck and/or low back pain.	Case based reasoning.	No significant difference in outcomes was found between participants using the personalized care app, a static informational website, and a control.
Anan et al. [23]: "Effects of an artificial intelligence–assisted health program on workers with neck/shoulder pain/stiffness and low back pain: randomized controlled trial"	Evaluate the effects of an AI-based health program delivered through a messaging app in workers with neck/shoulder pain/stiffness and lower back pain.	Randomized control trial.	94 individuals with neck/shoulder pain/stiffness and lower back pain.	Self-care app "Secaide".	Significant improvements in pain were seen in the group assigned to the app compared to the control (In the treatment group, 36 of 48 saw improvement, compared to 3 of 46 in control).
Snyder et al. [24]: "A deep learning approach for lower back-pain risk prediction during manual lifting"	Utilize kinematic sensor data in conjunction with deep learning algorithms to categorize lower back pain risk during lifting.	Retrospective analysis.	10 subjects performing manual lifting exercises.	Convolutional neural network (CNN).	The CNN was able to classify participants into low back pain risk groups with 90.6% accuracy using data from an accelerometer worn by the participant.
Knab et al. [25]: "The use of a computer-based decision support system facilitates primary care physicians' management of chronic pain"	Evaluate the ability of a computer-based decision support (CBDS) system to improve a primary care provider's (PCP) chronic pain management.	Prospective clinical trial.	50 patients with chronic pain.	Computer based decision support (CBDS) system.	CBDS system generated medically acceptable recommendations for the primary care providers in 85% of patients. The use of a CBDS may improve the ability for PCPs to treat chronic pain.
Cai et al. [26]: "Application of deep learning algorithms in automatic sonographic localization and segmentation of the median nerve: a systematic review and meta-analysis"	Determine the efficacy of artificial intelligence based perceptual learning when teaching medical residents to perform an ultrasound guided sciatic block.	Randomized control study in which residents were assigned to a traditional teaching group, and an AI teaching group where students practiced with an AI nerve identification system.	40 medical residents.	CNN.	Rates of pain during puncture and injection were significantly lower in the AI teaching group compared to the traditional group in the first month (2–4% vs. 14–16%). AI tools show promise as a means for learning pain medicine procedures.

*A sample of studies on applications of AI in improving treatment and pain maintenance.

The final and most cited application of AI in pain medicine is related to its use in the actual treatment of patients. Seven articles were reviewed that utilized a form of AI either in the direct treatment and rehabilitation of chronic pain or in an adjacent application such as administrative support. In terms of direct treatment, several different studies examined the efficacy of AI in personalizing and managing therapy for chronic pain patients.

One novel application was examined by Ortiz-Catalan et al. [20]. In this study, researchers sought to treat phantom limb pain using machine learning and virtual reality. The method by which they did this first involved using machine learning models to determine a patient's intended phantom limb movements from myoelectric patterns at the stump of the amputated limb. The technique is termed myoelectric pattern recognition (MPR) and can decode myoelectric signals in real time. The MPR data was then combined with augmented reality to provide visual feedback for the intended phantom limb movements. In effect, the patient could see themselves on a screen with their missing limb restored. Using phantom limb movements, the patient could then control the virtual limb and see movements in real time. Outcomes of the study were measured with the numeric rating scale (NRS), the pain rating index (PRI), and the weighted pain distribution scale (WPD). After 12 sessions with the AR interface, patients showed a 47% reduction in WPD, 32% reduction in NRS, and 51% reduction in PRI. The results of this study illustrate a promising treatment for PLP as well as an innovative application of AI within the field.

Alongside direct treatment, several studies investigated the use of AI as an administrative aid. One representative study was conducted by Piette et al. [21]. Researchers in the study sought to determine the efficacy of AI to assist therapists in delivering cognitive behavioral therapy for chronic pain. Interventions involved daily calls for 10 weeks in which an interactive voice response (IVR) call would gather feedback from patients. A machine learning model would then use this feedback to make a treatment recommendation for that week. Treatments involved either a thorough 45-min call with a therapist, a 15-min check-in call with the therapist, or an IVR call that delivered therapist notes. Results of the study showed non-inferior outcomes to the comparison group in which every patient received a weekly 45-min call. The results of this study are significant as the quality of outcomes in the AI-controlled group was maintained with less than half the therapist time compared to the control.

Discussion

Central Findings

Current applications of AI in pain medicine are seen at every step of chronic pain management. This includes initial diagnosis, treatment planning, and treatment/therapy performance. Each of these phases, however, varies in the quantity of research conducted and the success researchers are seeing.

When it comes to initial diagnosis, there have been mixed results. AI models have proven to be effective in differentiating different chronic pain-causing conditions, as well as stratifying patients on risk. Both can be useful when planning a treatment approach and improving patient outcomes. However, these models are by no means a comprehensive diagnostic tool. The studies reviewed only categorized patients into a few predetermined groups, such as high risk vs. low risk. The other commonly investigated diagnostic application involved attempting to leverage AI to objectively quantify pain. Approaches that were based on physiological data, such as biopotentials, saw success in using that data to accurately predict a patient's pain state. Other approaches that involved the use of pictures or footage of a patient's facial expressions as an indicator of pain were not as effective.

A common pattern across the reviewed studies involved the use of AI models for predicting future states. One of the primary uses, discussed previously, was for predicting a patient's pain progression. In this use case, there was significant success. In several studies, researchers were able to create models with the ability to accurately predict pain progression. A limit of these predictions, however, is they are categorical and only predict pain improvement vs. deterioration rather than quantifying said progressions. In conjunction with pain progression, AI models have proven to be effective in predicting a patient's treatment response. These predictions were limited to comparisons, such as which drug a patient would respond more strongly to, as well as predicting if patients were susceptible to placebo effects. None of the reviewed studies investigated or were successful predicting whether a patient would respond directly to a treatment or not. Nevertheless, the ability to accurately predict pain progression as well as compare treatment responses are valuable tools when developing treatment plans, including making decisions surrounding invasive interventions.

Lastly, there has been notable success in the use of AI models for treatment optimization and delivery. Within this scope, most of the pertinent studies involve the use of AI for the creation of physical therapy exercise plans that patients can do at home. The results of these studies showed generally better or non-inferior results when compared to conventional methods and involved greater personalization. Additionally, as discussed previously, AI models can be used in conjunction with other forms of technology such as augmented reality to create innovative new therapies and improve patient outcomes.

Research Gaps and Future Directions

One of the largest gaps in current research involves the lack of literature on nerve stimulation. No articles were identified that utilized AI in any effect related to nerve stimulation despite appearing to be a prime use case for AI in pain medicine. Every application of nerve stimulation is effectively its own optimization problem. Particularly in electrical stimulation, there can be multiple parameters that need to be set with the goal of minimizing a patient's pain. These parameters may include things such as electrical frequency, intensity, duration, and current pattern. While guidelines exist for these parameters, individual patients can respond differently to stimulation parameters, and in cases such as transcutaneous electrical nerve stimulation (TENS), a trial-and-error approach is taken that involves altering settings to maximize patient comfort [27]. Future research should investigate the use of AI in optimizing these neuromodulation parameters. Similar things have been done outside of chronic pain treatment. In a study by Boutet et al. [28], researchers tried utilizing machine learning and brain MRI scans to predict optimal deep brain stimulation parameters for the treatment of Parkinson's. Like TENS, determining the large number of parameters for deep brain stimulation can be time intensive and occurs over several clinical visits [28].

Extending on parameter optimization, future research should be conducted on the use of AI in creating closed-loop nerve stimulation systems. That is, a nerve stimulation system that can adjust its parameters without input from the patient. Closed loop systems have successfully been developed on a few occasions. Researchers Mekhail et al. [29] conducted a secondary analysis of an Evokes clinical trial of a closed-loop system and found positive patient outcomes relative to an open-loop system. However, no studies were identified that attempted to use AI models in developing and optimizing a closed-loop system. Research referenced in this review may also offer inspiration for different approaches to creating a closed-loop system. For example, in Gruss et al. [8] the use of machine learning applications in predicting pain levels could offer insights into methods for closed-loop systems obtaining feedback.

Another large gap in current research involves predicting treatment response. Current studies may act as a proof of concept for predicting differential responses to treatments. Future research should expand on this by developing models that can compare and predict response to a wider array of treatments. Additionally, opioid abuse is a major concern in the USA, with the country seeing over 42,000 opioid-related deaths in 2016 alone [30]. The use of AI models for predicting a patient's addiction risk could be useful in planning individualized pain treatments that minimize addiction risk. The ability to compare a range of treatments will allow providers to more effectively and efficiently create treatment plans that optimize patient outcomes.

Challenges and Limitations

One of the primary challenges in creating a well-performing AI model is access to data. Models are generally trained on large datasets. In the case of image recognition, for example, datasets can comprise upward of 100,000 labeled images [3]. Additionally, it is not always clear the features that need to be included in the dataset such that meaningful patterns can be identified. For instance, when attempting to train an AI model to predict a patient's response to a particular drug, researchers need to identify relevant patient features that the model can act on. Thus, one of the longstanding limitations of AI in medicine is the ability to gather large quantities of sufficiently complex and relevant data [3].

Other commonly cited limitations include the algorithms' susceptibility to bias and a lack of transparency. An AI-derived model is only as good as the data it was trained on, and if bias is present in the data, the model itself can hold these biases. Additionally, primarily when dealing with neural networks, the model may provide a prediction but not provide any details about how it arrived at said prediction. In this sense, neural networks have been described as black boxes lacking in transparency [1].

Conclusion

Current applications of AI in pain medicine show promising results that have the potential to significantly improve the quality of life for those living with chronic pain. That said, much of the existing research is concentrated on specific applications such as objective pain assessment and the delivery of personalized therapy. Future research should attempt to investigate a broader array of applications within the field, specifically in areas such as nerve stimulation, as well as translate the findings from retrospective studies into clinical trials where patient outcomes can be measured.

Author Contributions All authors participated in study design, drafting and writing

Compliance with Ethical Standard

Conflict of Interest The authors declare that they have no competing interests.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

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