



## Review Article

# The Amalgamation of artificial intelligence in regenerative orthopaedics: A narrative review

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## Abstract

Stem cells are undifferentiated cells that has the ability to form various types of functional cells, all the while retaining their inherent potential and originality. Modern medicine is moving towards replacing the damaged tissues rather than just treating the illness alone, like in the old times. Various studies are being conducted to explore the huge potential hidden in stem cells and to exploit their ability of regeneration into various types of cells in order to integrate them in the treatment process. Currently several fields of medicine including orthopedics are using stem cell therapy in different modalities of the treatment. Stem cells are the core in this new field of regenerative orthopedics (RO), which is ever evolving and the protocol of designing and implementation for a safe practice requires large data analysis in terms of their efficacy and ethical acceptance. Some data are too complex for the human mind to be done faster. Hence several computed programs and software are being created to analyze complex medical data and make the regenerative orthopedics an effective treatment. Artificial Intelligence (AI) has turned a new leaf in the field of science and medical world. The AI is still evolving with ongoing multiple researches and has unavoidable huge future prospects in the field of medicine. This article is an attempt to combine the application of artificial intelligence in the field of regenerative orthopedics in order to analyze the treatment, advantages, disadvantages, limitations and prospects.

**Keywords:** AI (Artificial Intelligence), RO (Regenerative Orthopedics), MSCs (Mesenchymal Stem Cells), ESCs (Embryonic Stem Cells), iPSCs (Induced Pluripotent Stem Cells)

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## 1. Introduction

Stem cells have infinite self-renewal potential that can differentiate into any type of cell in the body. Based on the ability of differentiation, the stem cells are classified as Totipotent (can form an entire organism- eg. Zygote), Pluripotent (can't form an entire organism but can differentiate into all types of cells-eg. Blastocyst), Multipotent (can form only a particular group of cells-eg. Mesenchymal stem cells), Unipotent (can form single cell type only-eg. Neuronal stem cells).<sup>1,2</sup> For ethical reasons, totipotent and pluripotent stem cells can't be used in the treatment. The multipotent stem cells (Mesenchymal stem cells – MSC derived from the bone marrow) are the most commonly used cells in regenerative orthopedics.<sup>3,4</sup> Fetal stem cells derived from umbilical cord, Wharton jelly, placenta, amniotic membrane have more efficacy than the stem cells obtained from adult bone marrow.<sup>5,6</sup> Studies are being done to use genetic engineering

to reprogram the differentiated cells into undifferentiated cells. Such artificially reprogrammed cells are called Induced Pluripotent Stem Cells (iPSC). Mesenchymal stem cells from bone marrow are induced by genetic reprogramming into pluripotent stem cells (iPSC) and from them attempts are being made to regenerate the human organ. Such organ regeneration avoids the complications related to transplant. Artificial intelligence plays a huge role in coding the genetic engineering protocols and makes it much easier to reprogram the cells.<sup>7,8</sup>

Artificial Intelligence is the science of making intelligent machines. The term was coined by John McCarthy in the year 1956.<sup>9</sup> AI is ever evolving with an ultimate motive to create machines with super human intelligence that are able to think, see, hear and act like a human being.<sup>10</sup>

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Such super human intelligence makes it easier to analyze any complex medical data that is difficult to analyze with human intelligence alone. This superhuman analysis is of great use in the diagnosis, treatment and prognosis in several clinical scenarios.<sup>11</sup> Despite the number of trials being done, there are several challenges and limitations being encountered. This article integrates AI and RO and makes it easier to study the advantages & disadvantages, challenges, limitations and their prospects.

## 2. Artificial Intelligence(AI)

Artificial intelligence is the machine intelligence that has revolutionized almost every industry which is virtually and physically implemented in the field of medicine. Virtual uses include gathering, storing, analyzing complex medical data records and find patterns that are beyond human capacity. Physical uses of AI include robotic surgeries, nanobot drug delivery and many upcoming researches.<sup>12</sup>

AI algorithms require comprehensive databases that include images, notes, genetic sequences, audio and video recording of patients. Such algorithms have been designed to establish precise diagnosis, select the target medications, minimizing the medical errors.<sup>13</sup> A diagnostic algorithm was designed for early diagnosis of breast cancer and implemented successfully.<sup>14</sup> With AI, machines can learn and improve over time, thereby can screen large number of patients faster and reducing the number of errors, saving lots of resources and human power.<sup>15</sup> AI enables machines to diagnose like human beings.<sup>16,17</sup> AI enables human specialists in making precise decisions.<sup>18</sup> Studying human brain is the key element to develop the computed programs and algorithms for contextual intelligence in AI.<sup>19</sup> Image and speech recognition is better performed with AI than humans alone.<sup>20</sup> AI can collect specific patterned information out of the vast majority of mixed data and help in clinical decision making.<sup>21</sup> AI speeds the entire workflow in the health care system.<sup>22</sup>

AI is implemented in early disease detection and found to easily diagnose the common diseases prevalent in the community.<sup>23</sup> A radiological screening tool is designed with AI and has yielded good results.<sup>24</sup> AI is used to track the cellular molecules, study multiple cellular interactions at the same time. AI was able to identify the modified and unmodified Epidermal Growth Factor Receptor. Thus, the biomarkers for several tumors can be identified earlier with help of AI.<sup>25</sup> Currently several illnesses don't have biomarkers and with AI this can be overcome in the future. Tuberculosis metabolite signatures which can forewarn the progression of the disease have been identified by AI.<sup>26</sup>

With the AI algorithms it is easy to design new molecules, determine their therapeutic dosage, side effects and toxic dose. This reduces the clinical drug research time, use of animals for lab testing and human power.<sup>27</sup> Many companies are using AI to research new molecular structures and find new drugs.<sup>28,29</sup> AI has been used to predict the patient

responses and setup right amount of check point inhibitors in the treatment of cancer with chemotherapy and radiotherapy.<sup>30</sup> The chemotherapy drugs and radiation interactions with the host tumor cells, normal cells are studied at bio-molecular level which helps in designing proper dosage protocols of the treatment.<sup>31</sup>

The applications of AI in regenerative medicine is the latest update in the field of AI. Since regenerative medicine is a novel field, there is much less data available which leads to increased use of resources and human error. Multiple tissue engineering models have been designed and tested. Robotic fabricated scaffolds are designed for setting up precise culture medium with proper consistency to co-culturing of different cells. The co-culturing of cells at different conditions needs to be identified to discover how an organ forms exactly. AI can help in structuring an algorithm to predict organ formation. Organ transplantation field is going to be having some major breakthroughs after the perfection of the organ forming AI algorithm.<sup>32,33,34</sup>

## 3. Regenerative Orthopedics(RO)

Mesenchymal stem cells are the backbone of regenerative orthopedics. The current researches focus on using MSCs in preclinical and clinical studies.<sup>35</sup> Three common focus areas of RO include - incorporating the MSCs into 3D scaffolds for tissue replacement in vivo using allogenic donor cells to replace the genetically mutant recipient cells thereby correcting the genetic defects; MSCs are used as a means to secrete cytokine/growth factors to enhance the repair of damaged tissues. These methods are tried in various animal models for achieving cartilage repair and bone regeneration and also implemented in the treatment of non-union, spinal fusions, bone cysts, osteonecrosis and various bone defects.<sup>36,37,38</sup>

Children with osteogenesis imperfecta are treated with MSC therapy and it is found to improve the bone growth velocity.<sup>39</sup> MSC therapy prevents functional bone loss in senile osteoporosis in animal model.<sup>40</sup> MSC cell therapy has given promising results in intervertebral disc degeneration in animal models.<sup>41</sup> The source of MSC has a controversy whether it could be from adipose tissue or the bone marrow.<sup>42</sup> A comparative study of adult equine mesenchymal stem cells derived from bone marrow and adipose tissue showed that the bone marrow derived MSC has good potential.<sup>43</sup> MSCs have very low yield capacity and if they are cultured for a long time, they lose their plasticity and undesired mutations occur. So short term culture is preferred for studies.<sup>44,45</sup>

Allogenic stem cells are better than autologous cells in elderly patients and patients with mutated MSCs as in osteoarthritis.<sup>46,47</sup> Mass production and ready availability is much better with allogenic stem cells. Studies show that immune reactions can occur in the recipient from donor allogenic stem cells.<sup>48</sup>

Pluripotent Embryonic Stem Cells (ESCs) have major ethical dilemma but are superior to MSC and studies are still being made for the use of ESCs in regenerative orthopedics.

ESCs derived from a mice and its injection around the injured spinal cord of that mice, suggested a good motor neuron recovery.<sup>49</sup> Equine ESCs differentiate into tenocytes with TGF- $\beta$ 3 stimulation.<sup>50</sup> We have a limited knowledge of ESCs biology and they are known to induce teratomas.<sup>51</sup> So we need to develop new protocols for using ESCs. Human ESCs extraction destroys the embryo, and it has huge ethical and religious dilemma. A new technique was developed to make pluripotent cells from fibroblasts by adding the transcription factors SOX2, c-MYC, KLF4 or OCT3/4. These cells were termed as induced pluripotent cells(iPSCs).<sup>52</sup> This technique has avoided the controversy of obtaining ESCs from embryo. iPSCs have been found to enhance chondrogenesis with the addition of growth factors and hence it has a good potential in regenerating cartilage in articular cartilage injuries.<sup>53</sup> A study has proved that chondrocytes can be generated from iPSCs derived from the peripheral blood.<sup>54</sup> One study has shown that iPSCs can be used for the treatment of spinal cord injuries.<sup>55</sup> iPSCs have been used in the treatment of macular degeneration<sup>56</sup> and Parkinson's disease.<sup>57</sup> Although iPSCs are cost effective and can be used without ethical issues when compared to the ESCs, they are still prone for genetic mutations which lead to tumorigenesis. So still research is being made to reduce the risk of mutations and to identify the cyclic mechanism.

Hematopoietic stem cells are multipotent cells derived from bone marrow and they are transplanted into patients with various types of malignant, non-malignant disorders and autoimmune diseases. In chemotherapy and radiotherapy these cells enhance the recovery of the patients.<sup>58</sup>

#### 4. Components of AI in Health Care

AI is not a single technology but a collection of several technologies. The five basic things of AI technology are learning, reasoning, problem-solving, perception, and language understanding.<sup>59</sup>

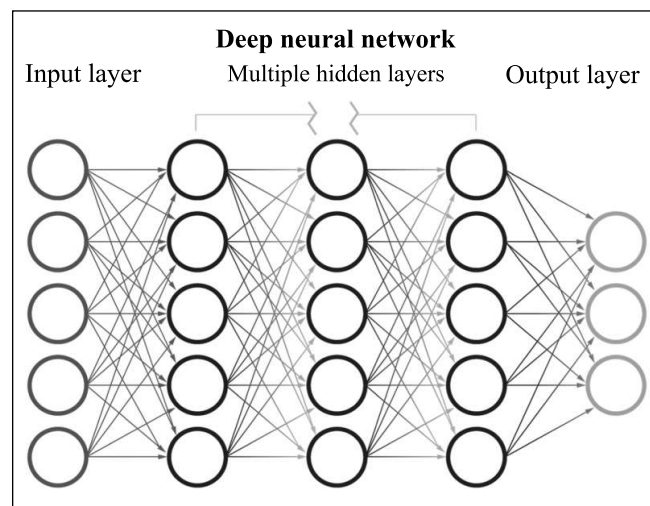
Important components of AI related to healthcare have been discussed here.

##### 4.1. Machine learning

Machine learning is the technique to make machines learn by training models with data and it is the most used form of AI. Several patient data including their clinical parameters, history and treatment aspects are entered into AI and the machine learns the pattern and develops the ability to predict the future outcome of patients. There are two types of machine learning which include supervised and unsupervised learning. In supervised learning, both input and output data are provided to the model whereas in the unsupervised learning, only input data is provided. The goal of supervised learning is to train the model so that it can predict the output when it is given a specific set of new data.<sup>60</sup>

Neural networks are a complex technology of Machine learning which not only view the problems in terms of variables of inputs, outputs and features but also makes several connections between those inputs, outputs and predicts an outcome just like neurons in the human brain.<sup>61</sup>

Deep learning is a type of neural network technology with multiple layers. Deep learning is mostly used in healthcare to recognize the potentially cancerous lesions in radiology images that are difficult to see with naked eye.<sup>62,63</sup>



**Figure 1:** Depiction of a deep neural network.

Source: <https://www.ibm.com/cloud/blog/ai-vs-machine-learning-vs-deep-learning-vs-neural-networks>

##### 4.2. Natural language processing

It is the ability of a machine to process and understand human language. This application helps in creating, perceiving, understanding and classifying the clinical documentation and published research. This requires large data of languages. They can analyze complex unstructured clinical notes comprising of large patient data and help in preparation of related reports such as radiological imaging. Medical transcription, doctor-patient interactions and several other aspects can be easily processed into data for further new patient treatment.

##### 4.3. Rule-based expert system

Expert systems are based on collections of rules like 'if-then'. Rule based expert system is mainly employed for supporting the clinical decision.<sup>63</sup> Electronic health record system is also a rule based expert system that stores a large data. Such rule based expert systems need the knowledge of human experts to design the rules pertaining to a particular field of knowledge. They are easy to understand and work well up to a certain number of rules. If the number of rules increases over several thousand, then the rules begin to contradict each other, which breaks down the entire system. Also, if the domain of a selected knowledge is changed, then the rules to be changed will become very tough and time consuming. Due to these shortcomings, the expert systems are being replaced slowly by data and machine learning protocols.

##### 4.4. Physical robots

Physical robots are known to everyone in the present world. The robots perform tasks that are pre-defined for them. Some of these tasks include lifting and repositioning of objects, even the welding or assembling of things at a factory, warehouse and they are also able to deliver bulk supplies to the hospital.

These robots have become increasingly collaborative with human tasks. Robots can be easily trained to perform any desired task. The robotic operating system is being installed with AI capabilities, and they are becoming more intelligent day by day. This operating system is like the human brain. So, we can expect robots to perform more like a human being in the near future.

Robotic assisted surgeries are being done at present with excellent precision than with human experts alone, though critical decisions are being made by surgeons.<sup>64</sup> Robotic surgeries are more commonly employed in joint replacement surgeries especially knee replacement.

#### 4.5. Robotic process automation

Administrative digital tasks with predefined script are being performed by machines just like a human user. This technology is called robotic process automation. Here just the computer programs and servers are needed, and an actual robot is not needed. So, this technology is less expensive when compared to other forms of AI. In the field of medicine, they are helpful for doing tasks in auto-repeat mode like booking appointments, updating patient bills and other data. Inputs can be extracted from images online or fax when this technology is combined with image recognition AI.<sup>65</sup>

These are the most used AI components in healthcare. Everyday research are being done to combine and integrate various other AI technologies and to use them in the medical field. With these new technologies, different combinations are being created and in future this may lead to solving more complex problems that are not feasible for human mind alone.

#### 4.6. Hierarchy of AI

1. **Algorithm:** They are automated instructions.
2. **AI:** Computers that mimic human intelligence.
3. **Machine learning:** AI + ability to learn new things
4. **Deep learning:** Machine Learning + self-learn the hidden patterns from huge data collection + training a model.
5. **Artificial neural networking:** Recognize patterns + process complex signals.
6. **Convolutional neural networking:** Image recognition and processing.

#### 4.7. AI-RO relationship

The regenerative orthopedics field has shortcomings in terms of huge data quantity, data analysis, methods to standardize techniques and human errors. The study of stem cell colony morphology is prone to human error and too difficult to accurately, especially in large culture studies. Attempts are being made to design an automated approach for analyzing the stem cell culture quality and segregation in order to bypass this shortcoming.<sup>66,67,68</sup> AI deep learning is used in stem cell culture to detect abnormal cells accurately, count the stem cells noninvasively, identifying the morphological and behavioral patterns of the cultured cells.<sup>69,70,71,72</sup> With

the help of AI, fiber based matrixes are being used to design 3D scaffolds with the help of tissue engineering by optimizing the piezoelectric property of bio-printing. This has paved a way for future bio-printing researches<sup>73,74</sup> in order to generate various new blueprints with which we can bio-print organs.<sup>75,76</sup>

AI can analyze the patient data and produce targeted patient specific biomaterials. With AI, the stem cell interactions and topology are studied and this application is used to find the reaction of stem cells in response to different stimuli, thereby the entire reaction cycle of the stem cell response can be studied.<sup>69</sup> An AI deep learning stem cell model can study the cell behavior elaborately than human brain, thus reducing the time and resources needed for such a large experiment.<sup>77,78</sup> Apart from topology, AI is used to determine stem cell differentiation, stem cell relation to the environment,<sup>79</sup> detecting the pluripotent cell growth and formation.<sup>80</sup> AI also provides the automated updates on stem cell colony quality control.<sup>81,82</sup> After culturing a good quality of stem cell colony, it is imperative to prevent the graft vs host disease. This chronic graft vs host reaction is the leading cause of failure in stem cell therapy.<sup>83</sup> Without AI it is almost impossible for human specialists to identify the exact phenotype marker that causes graft vs host disease in the recipient of stem cell therapy.<sup>84</sup> AI can identify all the specific phenotypes that cause graft vs host disease and design a flow chart for decision making easily. In acute leukemia such decision-making flowchart was made with AI predictions to identify the stem cell mortality rate.<sup>85</sup> AI has minimized animal experimentation with its accurate predictions.<sup>86</sup> Following are some of the studies made to integrate AI with stem cell therapy.

1. Kavita et al.<sup>87</sup> used complex neural network AI to illustrate the features of stem cell colony, based on the descriptor extraction of the iPSC colony, and found 95.5% accuracy.
2. Kusumoto and Yuasa et al.<sup>88</sup> used complex neural network AI to identify iPSC derived endothelial cells without labelling any molecule and produced results of high prediction.
3. Waisman et al.<sup>89</sup> showed that complex neural network can identify the differentiated and undifferentiated stem cells and distinguish them with 99% accuracy.
4. Nishino et al.<sup>90</sup> used trained AI models to identify the distinguished epigenetic signatures of iPSCs with 94.2% accuracy.
5. Yu Yang et al.<sup>91</sup> demonstrated that an optimal implantation of about 17–25 million MSCs can treat patients with cartilage damages with a reliable result.
6. Joseph et al.<sup>92</sup> designed AI algorithms that are used for classification of OA knee with the help of imaging and non-imaging-based Machine Learning models with good reliable results.

Joint cartilage is invisible in plain radiographs. So, the cartilage loss is assessed indirectly by measuring the joint space. In 1989 computerized software was developed to

measure joint space in the hand<sup>93</sup> and knee.<sup>94</sup> At present an AI software is developed to automatically measure the wrist joint space.<sup>95</sup>

AI software measures the cartilage volume and thickness in MRI with good accuracy.<sup>96</sup> Deep learning methods are designed to accurately measure and detect even minimal damage to the knee cartilage,<sup>97</sup> and the methods are even further advanced recently to classify the different varieties of cartilage lesions.<sup>98</sup>

Used 3D convolutional neural network for scoring the severity of knee lesion and found that the method had high sensitivity, specificity, and accuracy.<sup>99</sup> Lok Sze Lee et al.<sup>100</sup> in their study used AI to detect osteoarthritis of knee and found it to be helpful in planning preoperative strategies for knee replacement surgery. The main drawback is that once the protocols are designed, any further addition of variables changes the result and so furthermore research are needed to overcome such limitations.

Shaohui Wang et al.<sup>101</sup> developed an AI assisted deep learning and cloud computing conceptual model for the diagnosis of Rheumatoid disease and cartilage damage. Perni et al.<sup>102</sup> introduced AI based poly-beta-amino-esters (PBAEs) in order to deliver the desired drugs into the damaged cartilage tissues for treatment. On repeating the procedure with optimal concentration, it is found that certain PBAEs improve the drug uptake more than 20 folds when compared to the routine clinical treatment.

#### 4.8. Future prospects

AI has tremendous potential in the future health care revolution. especially in the field of regenerative medicine. Some of the following developments are expected in the future of AI. Pharmacology industry is to be revolutionized by AI.<sup>103</sup> AI programs design new drugs in less time, with decreased animal testing and with less human power and resources. New antibiotics, analgesics and several other drugs are to be waited for our use. AI can even discover newer materials that mimic human cartilage and even a human organ. Cartilage, bone and organ replacements are difficult at present due to scarcity and donor-recipient cross reactions. In future, with the development of AI all these shortcomings can be easily overcome. AI can give us a good biochemical design of implants<sup>104</sup> with controlled degradation rate and hence a second surgery for implant removal can be avoided. Biodegradation of collagen scaffolds can be controlled by AI till we achieve the desired incorporation of that scaffold into the native tissues. Newer scaffolds of materials are identified by AI, like the Polycaprolactone (PCL).

Polycaprolactone mesh can be made into a scaffold using AI and incorporated with Beta-Tricalcium Phosphate and when this combination is cultured with the pre-osteoblasts of mouse, it is found that there is increased collagen synthesis and mineralization which is much like that of the native bone-cartilage interface. Enhanced healing rate is also observed.<sup>105</sup>

Single stem cell biophysical and biochemical properties may be found in-toto with the help of AI by studying the nano topographical effect on single cell function.<sup>106</sup> Once the behavioral response of stem cells are studied, the stem cell promoters and enhancers can be developed to achieve the desired response from stem cell therapy. AI research can be interlinked to achieve a unique database, so that all the AI researchers can benefit from this database with more information and less time consumption.

Deep Learning and neural networks are going to be integrated into the research and clinical applications in the future which is going to change the entire health care industry especially in the human biologics, tissue engineering and regenerative orthopedics.

## 5. Limitations

The focus of this study is about the various aspects of AI application in regenerative orthopedics with a keen focus on stem cell therapy. We have discussed an overview of AI in stem cell therapy and the detailed analysis of each specific subtype of AI is beyond the scope of this paper.

## 6. Conclusion

Regenerative orthopedics is an important branch in the field of regenerative medicine and it is becoming more and more important to find newer innovations. This is mainly due to the rising geriatric population across the whole world. Machine intelligence is taken to the next level by AI. Though AI has revolutionized the field of regenerative orthopedics with numerous successful developments, still there are many more hurdles in the future path especially with creating a perfect design of biomaterials and a complete understanding of stem cell biophysical and biochemical interactions.

The exact genetics that influence the formation of a particular organ is essential to be discovered, in order to harness the full use of AI in reconstructing new organs and replacing the damaged organs. With AI, the current challenges are being tackled one by one and we are marching forwards to patient-specific and trauma-specific biomaterials. Hence the future of bone regeneration belongs to AI. But still AI is at its primitive point with regards to the knowledge and still more research are to be done for a detailed understanding about the relationship between AI and RO.

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Self.

## 9. Conflict of Interest

None.

## References

1. Bissels U, Diener Y, Eckardt D, Bosio A. Characterization and classification of stem cells. In: *Regenerative Medicine—from Protocol to Patient: 2. Stem Cell Science and Technology 2016* (pp. 1–25). Cham: Springer International Publishing.
2. Bacakova L, Zarubova J, Travnickova M, Musilkova J, Pajorova J, Slepicka P, et al. Stem cells: Their source, potency and use in regenerative therapies with focus on adipose-derived stem cells – A review. *Biotechnol Adv.* 2018;36(4):1111–26. <https://doi.org/10.1016/j.biotechadv.2018.03.011>
3. Noguchi H, Saitoh I, Tsugata T, Kataoka H, Watanabe M, Noguchi Y. Induction of tissue-specific stem cells by reprogramming factors, and tissue-specific selection. *Cell Death Differ.* 2015;22(1):145–55. <https://doi.org/10.1038/cdd.2014.132>
4. Ullah I, Subbarao RB, Rho GJ. Human mesenchymal stem cells: Current trends and future prospective. *Biosci Rep.* 2015;35(2):e00191. <https://doi.org/10.1042/BSR20150025>
5. Zakrzewski W, Dobrzyński M, Szymonowicz M, Rybak Z. Stem cells: Past, present, and future. *Stem Cell Res Ther.* 2019;10(1):68. <https://doi.org/10.1186/s13287-019-1165-5>
6. Abdulrazzak H, Moschidou D, Jones G, Guillot PV. Biological characteristics of stem cells from foetal, cord blood and extraembryonic tissues. *J R Soc Interface.* 2010;7(6):S689–706. <https://doi.org/10.1098/rsif.2010.0347.focus>
7. Takahashi J. Strategies for bringing stem cell-derived dopamine neurons to the clinic: The Kyoto trial. *Prog Brain Res* 2017; 230: 213–26. <https://doi.org/10.1016/bs.pbr.2016.11.004>
8. Galipeau J, Sensébé L. Mesenchymal Stromal Cells: Clinical Challenges and Therapeutic Opportunities. *Cell Stem Cell.* 2018;22(6):824–833. <https://doi.org/10.1016/j.stem.2018.05.004>
9. Notes on artificial intelligence, machine learning and deep learning for curious people [Internet]. 2019 [cited 2021 Oct 16]. Available from: <https://towardsdatascience.com/notes-on-artificial-intelligence-ai-machine-learning-ml-and-deep-learning-dl-for-56e51>
10. Ahuja AS. The impact of artificial intelligence in medicine on the future role of the physician. *PeerJ.* 2019;7:e7702. <https://doi.org/10.7717/peerj.7702>
11. Ramesh AN, Kambhampati C, Monson JR, Drew PJ. Artificial intelligence in medicine. *Ann R Coll Surg Engl.* 2004;86(5):334–8. <https://doi.org/10.1308/147870804290>
12. Larijani B, Esfahani EN, Amini P, Nikbin B, Alimoghaddam K, Amiri S, et al. Stem cell therapy in treatment of different diseases. *Acta Med Iran.* 2012;50(2):79–96
13. Amisha, Malik P, Pathania M, Rathaur VK. Overview of artificial intelligence in medicine. *J Family Med Prim Care.* 2019;8(7):2328–31. [https://doi.org/10.4103/jfmpc.jfmpc\\_440\\_19](https://doi.org/10.4103/jfmpc.jfmpc_440_19)
14. Akselrod-Ballin A, Chorev M, Shoshan Y, Spiro A, Hazan A, Melamed R, et al. Predicting breast cancer by applying deep learning to linked health records and mammograms. *Radiology.* 2019;292(2):331–42. <https://doi.org/10.1148/radiol.2019182622>
15. Chen CT, Ackerly DC, Gottlieb G. Transforming healthcare delivery: Why and how accountable care organizations must evolve. *J Hosp Med.* 2016;11(9):658–61. <https://doi.org/10.1002/jhm.2589>
16. Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, et al. Dermatologist-level classification of skin cancer with deep neural networks. *Nature.* 2017;542(7639):115–18. <https://doi.org/10.1038/nature21056>. Erratum in: *Nature.* 2017;546(7660):686. <https://doi.org/10.1038/nature22985>
17. Kermany DS, Goldbaum M, Cai W, Valentim CCS, Liang H, Baxter SL, et al. Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning. *Cell.* 2018;172(5):1122–1131.e9. <https://doi.org/10.1016/j.cell.2018.02.010>
18. Coudray N, Ocampo PS, Sakellaropoulos T, Narula N, Snuderl M, Fenyö D, et al. Classification and mutation prediction from non-small cell lung cancer histopathology images using deep learning. *Nat Med.* 2018;24(10):1559–67. <https://doi.org/10.1038/s41591-018-0177-5>
19. Hassabis D, Kumaran D, Summerfield C, Botvinick M. Neuroscience-Inspired Artificial Intelligence. *Neuron.* 2017;95(2):245–58. <https://doi.org/10.1016/j.neuron.2017.06.011>
20. Hu J, Shen L, Sun G. Squeeze-and-excitation networks. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*; 2018. p. 7132–41. Available from: <https://arxiv.org/abs/1709.01500>
21. Moebus S, Kuhn J, Hoffmann W. Big Data und Public Health [Big Data and Public Health - Results of the Working Group 1 of the Forum Future Public Health, Berlin 2016]. *Gesundheitswesen.* 2017;79(11):901–5. German. <https://doi.org/10.1055/s-0043-118529>
22. Jiang F, Jiang Y, Zhi H, Dong Y, Li H, Ma S, et al. Artificial intelligence in healthcare: past, present and future. *Stroke Vasc Neurol.* 2017;2(4):230–243. <https://doi.org/10.1136/svn-2017-000101>
23. Dande P, Samant P. Acquaintance to artificial neural networks and use of artificial intelligence as a diagnostic tool for tuberculosis: A review. *Tuberculosis (Edinb).* 2018;108:1–9. <https://doi.org/10.1016/j.tube.2017.09.006>
24. Park SH, Han K. Methodologic guide for evaluating clinical performance and effect of artificial intelligence technology for medical diagnosis and prediction. *Radiology.* 2018;286(3):800–9. <https://doi.org/10.1148/radiol.2017171920>
25. Yasui M, Hiroshima M, Kozuka J, Sako Y, Ueda M. Automated single-molecule imaging in living cells. *Nat Commun.* 2018;9(1):3061. <https://doi.org/10.1038/s41467-018-05524-7>
26. Weiner J 3rd, Maertzdorf J, Sutherland JS, Duffy FJ, Thompson E, Suliman S, et al. Metabolite changes in blood predict the onset of tuberculosis. *Nat Commun.* 2018;9(1):5208. <https://doi.org/10.1038/s41467-018-07635-7>
27. Thomford NE, Senthilane DA, Rowe A, Munro D, Seele P, Maroyi A, et al. Natural Products for Drug Discovery in the 21st Century: Innovations for Novel Drug Discovery. *Int J Mol Sci.* 2018;19(6):1578. <https://doi.org/10.3390/ijms19061578>
28. Dzobo K. Epigenomics-guided drug development: Recent advances in solving the cancer treatment “jigsaw puzzle”. *OMICS.* 2019;23(2):70–85.
29. Hie B, Cho H, Berger B. Realizing private and practical pharmacological collaboration. *Science.* 2018;362(6412):347–350. <https://doi.org/10.1126/science.aat4807>
30. Poleszczuk J, Enderling H. The Optimal Radiation Dose to Induce Robust Systemic Anti-Tumor Immunity. *Int J Mol Sci.* 2018;19(11):3377. <https://doi.org/10.3390/ijms19113377>
31. Burkholder B, Huang RY, Burgess R, Luo S, Jones VS, Zhang W, et al. Tumor-induced perturbations of cytokines and immunecellnetworks. *BiochimBiophysActa.* 2014;1845(2):182–201. <https://doi.org/10.1016/j.bbcan.2014.01.004>
32. Durant F, Lobo D, Hammelman J, Levin M. Physiological controls of large-scale patterning in planarian regeneration: A molecular and computational perspective on growth and form. *Regeneration (Oxf).* 2016;3(2):78–102. <https://doi.org/10.1002/reg.2.54>
33. Kwee E, Herderick EE, Adams T, Dunn J, Germanowski R, Krakosh F, et al. Integrated colony imaging, analysis, and selection device for regenerative medicine. *SLAS Technol.* 2017;22(2):217–23. <https://doi.org/10.1177/2211068216676587>
34. Sniecinski I, Seghatchian J. Artificial intelligence: A joint narrative on potential use in pediatric stem and immune cell therapies and regenerative medicine. *Transfus Apher Sci.* 2018;57(3):422–4. <https://doi.org/10.1016/j.transci.2018.05.004>
35. Caplan AI. Review: mesenchymal stem cells: cell-based reconstructive therapy in orthopedics. *Tissue Eng.* 2005;11(7–8):1198–211. <https://doi.org/10.1089/ten.2005.11.1198>
36. Zamzam MM, Abak AA, Bakarman KA, Al-Jassir FF, Khoshhal KI, Zamzami MM. Efficacy of aspiration and autogenous bone marrow injection in the treatment of simple bone cysts. *Int Orthop.* 2009;33(5):1353–8. <https://doi.org/10.1007/s00264-008-0619-7>
37. Hesnigou P, Poignard A, Zilber S, Rouard H. Cell therapy of hip osteonecrosis with autologous bone marrow grafting. *Indian J Orthop.* 2009;43(1):40–5. <https://doi.org/10.4103/0019-5413.45322>

38. Shafiee A, Soleimani M, Chamheidari GA, Seyedjafari E, Dodel M, Atashi A, et al. Electrospun nanofiber-based regeneration of cartilage enhanced by mesenchymal stem cells. *J Biomed Mater Res A*. 2011;99(3):467–78. <https://doi.org/10.1002/jbma.a.33206>
39. Horwitz EM, Gordon PL, Koo WK, Marx JC, Neel MD, McNall RY, et al. Isolated allogeneic bone marrow-derived mesenchymal cells engraft and stimulate growth in children with osteogenesis imperfecta: Implications for cell therapy of bone. *Proc Natl Acad Sci U S A*. 2002;99(13):8932–7. <https://doi.org/10.1073/pnas.132252399>
40. Kiernan J, Hu S, Grynopas MD, Davies JE, Stanford WL. Systemic Mesenchymal stromal cell transplantation prevents functional bone loss in a mouse model of age-related osteoporosis. *Stem Cells Transl Med*. 2016;5(5):683–93. <https://doi.org/10.5966/sctm.2015-0231>
41. Crevensten G, Walsh AJ, Ananthakrishnan D, Page P, Wahba GM, Lotz JC, et al. Intervertebral disc cell therapy for regeneration: mesenchymal stem cell implantation in rat intervertebral discs. *Ann Biomed Eng*. 2004;32(3):430–4. <https://doi.org/10.1023/b:abme.0000017545.84833.7c>
42. Frisbie DD, Kisiday JD, Kawcak CE, Werpy NM, McIlwraith CW. Evaluation of adipose-derived stromal vascular fraction or bone marrow-derived mesenchymal stem cells for treatment of osteoarthritis. *J Orthop Res*. 2009;27(12):1675–80. <https://doi.org/10.1002/jor.20933>
43. Vidal MA, Robinson SO, Lopez MJ, Paulsen DB, Borkhsenius O, Johnson JR, et al. Comparison of chondrogenic potential in equine mesenchymal stromal cells derived from adipose tissue and bone marrow. *Vet Surg*. 2008;37(8):713–24. <https://doi.org/10.1111/j.1532-950X.2008.00462.x>
44. Roemeling-van Rhijn M, de Klein A, Douben H, Pan Q, van der Laan LJ, Ijzermans JN, et al. Culture expansion induces nontumorigenic aneuploidy in adipose tissue-derived mesenchymal stromal cells. *Cytotherapy*. 2013;15(11):1352–61. <https://doi.org/10.1016/j.jcyt.2013.07.004>
45. Chen G, Yue A, Ruan Z, Yin Y, Wang R, Ren Y, et al. Monitoring the biology stability of human umbilical cord-derived mesenchymal stem cells during long-term culture in serum-free medium. *Cell Tissue Bank*. 2014;15(4):513–21. <https://doi.org/10.1007/s10561-014-9420-6>
46. Broberg K, Höglund M, Lindstrand A, Toksvig-Larsen S, Mandahl N, Mertens F. Polyclonal expansion of cells with trisomy 7 in synovia from patients with osteoarthritis. *Cytogenet Cell Genet*. 1998;83(1–2):30–4. <https://doi.org/10.1159/000015160>
47. Zhou S, Greenberger JS, Epperly MW, Goff JP, Adler C, Leboff MS, et al. Age-related intrinsic changes in human bone-marrow-derived mesenchymal stem cells and their differentiation to osteoblasts. *Aging Cell*. 2008;7(3):335–43. <https://doi.org/10.1111/j.1474-9726.2008.00377.x>
48. Huang XP, Sun Z, Miyagi Y, McDonald Kinkaid H, Zhang L, Weisel RD, et al. Differentiation of allogeneic mesenchymal stem cells induces immunogenicity and limits their long-term benefits for myocardial repair. *Circulation*. 2010;122(23):2419–29. <https://doi.org/10.1161/CIRCULATIONAHA.110.955971>
49. Bottai D, Cigognini D, Madaschi L, Adami R, Nicora E, Menarini M, et al. Embryonic stem cells promote motor recovery and affect inflammatory cell infiltration in spinal cord injured mice. *Exp Neurol*. 2010;223(2):452–63. <https://doi.org/10.1016/j.expneurol.2010.01.010>
50. Barsby T, Guest D. Transforming growth factor beta3 promotes tendon differentiation of equine embryo-derived stem cells. *Tissue Eng Part A*. 2013;19(19–20):2156–65. <https://doi.org/10.1089/ten.TEA.2012.0372>
51. Chen Y, Lai D. Pluripotent states of human embryonic stem cells. *Cell Reprogram*. 2015;17(1):1–6. <https://doi.org/10.1089/cell.2014.0061>
52. Thomson JA, Itskovitz-Eldor J, Shapiro SS, Waknitz MA, Swiergiel JJ, Marshall VS, et al. Embryonic stem cell lines derived from human blastocysts. *Science*. 1998;282(5391):1145–7. <https://doi.org/10.1126/science.282.5391.1145>. Erratum in: *Science* 1998;282(5395):1827
53. Yang SL, Harnish E, Leeuw T, Dietz U, Batchelder E, Wright PS, et al. Compound screening platform using human induced pluripotent stem cells to identify small molecules that promote chondrogenesis. *Protein Cell*. 2012;3(12):934–42. <https://doi.org/10.1007/s13238-012-2107-5>
54. Li Y, Liu T, Van Halm-Lutterodt N, Chen J, Su Q, Hai Y. Reprogramming of blood cells into induced pluripotent stem cells as a new cell source for cartilage repair. *Stem Cell Res Ther*. 2016;7:31. <https://doi.org/10.1186/s13287-016-0290-7>
55. Nakamura M, Okano H. Cell transplantation therapies for spinal cord injury focusing on induced pluripotent stem cells. *Cell Res*. 2013;23(1):70–80. <https://doi.org/10.1038/cr.2012.171>
56. Okano T, Sawa Y, Barber E, Umezawa A. Regenerative therapy by fusion of medicine and engineering: First-in-human clinical trials with induced pluripotent stem cells and cell sheet technology: A report of the Symposium of Regenerative Medicine for Patients. *Regen Ther*. 2015;2:2–5. <https://doi.org/10.1016/j.reth.2015.07.002>
57. Schweitzer JS, Song B, Herrington TM, Park TY, Lee N, Ko S, et al. Personalized iPSC-Derived Dopamine Progenitor Cells for Parkinson's Disease. *N Engl J Med*. 2020;382(20):1926–32. <https://doi.org/10.1056/NEJMoa1915872>
58. Barriga F, Ramirez P, Wietstruck A, Rojas N. Hematopoietic stem cell transplantation: clinical use and perspectives. *Biol Res*. 2012;45(3):307–16. <https://doi.org/10.4067/S0716-97602012000300012>
59. Sarker IH. AI-Based Modeling: Techniques, Applications and Research Issues Towards Automation, Intelligent and Smart Systems. *SN Comput Sci*. 2022;3(2):158. <https://doi.org/10.1007/s42979-022-01043-x>
60. Lee SI, Celik S, Logsdon BA, Lundberg SM, Martins TJ, Oehler VG, et al. A machine learning approach to integrate big data for precision medicine in acute myeloid leukemia. *Nat Commun*. 2018;9(1):42. <https://doi.org/10.1038/s41467-017-02465-5>
61. Sordo M. Introduction to neural networks in healthcare. Open clinical: Knowledge management for medical care. 2002:1–7. Available from: [https://www.researchgate.net/profile/Margarita-Sordo/publication/228820949\\_Introduction\\_to\\_neural\\_networks\\_in\\_healthcare/links/65b0525f6c7ad06ab42615ee/Introduction-to-neural-networks-in-healthcare.pdf](https://www.researchgate.net/profile/Margarita-Sordo/publication/228820949_Introduction_to_neural_networks_in_healthcare/links/65b0525f6c7ad06ab42615ee/Introduction-to-neural-networks-in-healthcare.pdf)
62. Fakoor R, Ladhak F, Nazi A, Huber M. Using deep learning to enhance cancer diagnosis and classification. In: Proceedings of the International Conference on Machine Learning; 2013. New York (NY): ACM. p. 3937–3949.
63. Vial A, Stirling D, Field M, Ros M, Ritz C, Carolan M, et al. The role of deep learning and radiomic feature extraction in cancer-specific predictive modelling: A review. *Transl Cancer Res*. 2018;7(3).
64. Davenport TH, Glaser J. Just-in-time delivery comes to knowledge management. *Harvard business review*. 2002;80(7):107–1.
65. Hussain A, Malik A, Halim MU, Ali AM. The use of robotics in surgery: a review. *Int J Clin Pract*. 2014;68(11):1376–82. <https://doi.org/10.1111/ijcp.12492>
66. Kumar R, Sharma A, Siddiqui MH, Tiwari RK. Prediction of Metabolism of Drugs using Artificial Intelligence: How far have we reached? *Curr Drug Metab*. 2016;17(2):129–41. <https://doi.org/10.2174/1389200216666151103121352>
67. Kumar R, Sharma A, Siddiqui MH, Tiwari RK. Prediction of Human Intestinal Absorption of Compounds Using Artificial Intelligence Techniques. *Curr Drug Discov Technol*. 2017;14(4):244–54. <https://doi.org/10.2174/1570163814666170404160911>
68. Kumar R, Sharma A, Siddiqui MH, Tiwari RK. Promises of Machine Learning Approaches in Prediction of Absorption of Compounds. *Mini Rev Med Chem*. 2018;18(3):196–207. <https://doi.org/10.2174/1389557517666170315150116>
69. Mackay BS, Praeger M, Grant-Jacob JA, Kanczler J, Eason RW, Oreffo ROC, et al. Modeling adult skeletal stem cell response to laser-machined topographies through deep learning. *Tissue Cell*. 2020;67:101442. <https://doi.org/10.1016/j.tice.2020.101442>

70. Moen E, Bannon D, Kudo T, Graf W, Covert M, Van Valen D. Deep learning for cellular image analysis. *Nat Methods*. 2019;16(12):1233–46. <https://doi.org/10.1038/s41592-019-0403-1>
71. Havaei M, Davy A, Warde-Farley D, Biard A, Courville A, Bengio Y, et al. Brain tumor segmentation with Deep Neural Networks. *Med Image Anal*. 2017;35:18–31. <https://doi.org/10.1016/j.media.2016.05.004>
72. Lerouge J, Hérault R, Chatelain C, Jardin F, Modzelewski R. IODA: An input/output deep architecture for image labeling. *Pattern Recognit*. 2015 Sep 1;48(9):2847–58.
73. Tourlomis F, Jia C, Karydis T, Mershin A, Wang H, Kalyon DM, et al. Machine learning metrology of cell confinement in melt electrowritten three-dimensional biomaterial substrates. *Microsyst Nanoeng*. 2019;5:15. <https://doi.org/10.1038/s41378-019-0055-4>
74. Shi J, Song J, Song B, Lu WF. Multi-objective optimization design through machine learning for drop-on-demand bioprinting. *Engineering*. 2019;5(3):586–93.
75. Kim J, McKee JA, Fontenot JJ, Jung JP. Engineering tissue fabrication with machine intelligence: Generating a blueprint for regeneration. *Front Bioeng Biotechnol*. 2020;7:443. <https://doi.org/10.3389/fbioe.2019.00443>
76. Ng WL, Chan A, Ong YS, Chua CK. Deep learning for fabrication and maturation of 3D bioprinted tissues and organs. *Virtual Phys Prototyp*. 2020;15(3):340–58.
77. Matsuoka F, Takeuchi I, Agata H, Kagami H, Shiono H, Kiyota Y, et al. Morphology-based prediction of osteogenic differentiation potential of human mesenchymal stem cells. *PLoS One*. 2013;8(2):e55082. <https://doi.org/10.1371/journal.pone.0055082>
78. Williams B, Löbel W, Finklea F, Halloin C, Ritzenhoff K, Manstein F, et al. Prediction of Human Induced Pluripotent Stem Cell Cardiac Differentiation Outcome by Multifactorial Process Modeling. *Front Bioeng Biotechnol*. 2020;8:851. <https://doi.org/10.3389/fbioe.2020.00851>
79. Chen D, Sarkar S, Candia J, Florczyk SJ, Bodhak S, Driscoll MK, et al. Machine learning based methodology to identify cell shape phenotypes associated with microenvironmental cues. *Biomaterials*. 2016;104:104–18. <https://doi.org/10.1016/j.biomaterials.2016.06.040>
80. Fan K, Zhang S, Zhang Y, Lu J, Holcombe M, Zhang X. A machine learning assisted, label-free, non-invasive approach for somatic reprogramming in induced pluripotent stem cell colony formation detection and prediction. *Sci Rep*. 2017;7(1):13496.
81. Orita K, Sawada K, Matsumoto N, Ikegaya Y. Machine-learning-based quality control of contractility of cultured human-induced pluripotent stem-cell-derived cardiomyocytes. *Biochem Biophys Res Commun*. 2020;526(3):751–55. <https://doi.org/10.1016/j.bbrc.2020.03.141>
82. Joutsijoki H, Haponen M, Rasku J, Aalto-Setälä K, Juhola M. Machine learning approach to automated quality identification of human induced pluripotent stem cell colony images. *Comput Math Methods Med*. 2016;2016:3091039. <https://doi.org/10.1155/2016/3091039>
83. Arora M, Cutler CS, Jagasia MH, Pidala J, Chai X, Martin PJ, et al. Late Acute and Chronic Graft-versus-Host Disease after Allogeneic Hematopoietic Cell Transplantation. *Biol Blood Marrow Transplant*. 2016;22(3):449–55. <https://doi.org/10.1016/j.bbmt.2015.10.018>
84. Gandelman JS, Byrne MT, Mistry AM, Polikowsky HG, Diggins KE, Chen H, et al. Machine learning reveals chronic graft-versus-host disease phenotypes and stratifies survival after stem cell transplant for hematologic malignancies. *Haematologica*. 2019;104(1):189–196. <https://doi.org/10.3324/haematol.2018.193441>
85. Shouval R, Labopin M, Bondi O, Mishan-Shamay H, Shimoni A, Ciceri F, et al. Prediction of allogeneic hematopoietic stem-cell transplantation mortality 100 days after transplantation using a machine learning algorithm: A European group for blood and marrow transplantation acute leukemia working party retrospective data mining study. *J Clin Oncol*. 2015;33(28):3144–51. <https://doi.org/10.1200/JCO.2014.59.1339>
86. Hulsart-Billström G, Dawson JI, Hofmann S, Müller R, Stoddart MJ, Alini M, et al. A surprisingly poor correlation between in vitro and in vivo testing of biomaterials for bone regeneration: results of a multicentre analysis. *Eur Cell Mater*. 2016;31:312–22. <https://doi.org/10.22203/ecm.v031a20>
87. Kavitha MS, Kurita T, Park SY, Chien SI, Bae JS, Ahn BC. Deep vector-based convolutional neural network approach for automatic recognition of colonies of induced pluripotent stem cells. *PLoS One*. 2017; 12: e0189974. <https://doi.org/10.1371/journal.pone.0189974>
88. Kusumoto D, Yuasa S. The application of convolutional neural network to stem cell biology. *Inflamm Regen*. 2019;39:14. <https://doi.org/10.1186/s41232-019-0103-3>
89. Waisman A, La Greca A, Möbbs AM, Scarafia MA, Santin Velazque NL, Neiman G, et al. Deep Learning Neural Networks Highly Predict Very Early Onset of Pluripotent Stem Cell Differentiation. *Stem Cell Reports*. 2019;12(4):845–59. <https://doi.org/10.1016/j.stemcr.2019.02.004>
90. Nishino K, Takasawa K, Okamura K, Arai Y, Sekiya A, Akutsu H, et al. Identification of an epigenetic signature in human induced pluripotent stem cells using a linear machine learning model. *Hum Cell*. 2021;34(1):99–110. <https://doi.org/10.1007/s13577-020-00446-3>
91. Liu YYF, Lu Y, Oh S, Conduit GJ. Machine learning to predict mesenchymal stem cell efficacy for cartilage repair. *PLoS Comput Biol*. 2020;16(10):e1008275. <https://doi.org/10.1371/journal.pcbi.1008275>
92. Joseph GB, McCulloch CE, Sohn JH, Padoia V, Majumdar S, Link TM. AI MSK clinical applications: cartilage and osteoarthritis. *Skeletal Radiol*. 2022;51(2):331–43. <https://doi.org/10.1007/s00256-021-03909-2>
93. Allander E, Forsgren PO, Pettersson H, Seideman P. Computerized assessment of radiological changes of the hand in rheumatic diseases. *Scand J Rheumatol*. 1989;18(5):291–6. <https://doi.org/10.3109/03009748909095032>
94. Dacre JE, Huskisson EC. The automatic assessment of knee radiographs in osteoarthritis using digital image analysis. *Br J Rheumatol*. 1989;28(6):506–10. <https://doi.org/10.1093/rheumatology/28.6.506>
95. Huo Y, Vincken KL, van der Heijde D, de Hair MJH, Lafeber FP, Viergever MA. Automatic Quantification of Radiographic Wrist Joint Space Width of Patients With Rheumatoid Arthritis. *IEEE Trans Biomed Eng*. 2017;64(11):2695–703. <https://doi.org/10.1109/TBME.2017.2659223>
96. Eckstein F, Peterfy C. A 20 years of progress and future of quantitative magnetic resonance imaging (qMRI) of cartilage and articular tissues-personal perspective. *Semin Arthritis Rheum*. 2016;45(6):639–47. <https://doi.org/10.1016/j.semarthrit.2015.11.005>
97. Prasoon A, Petersen K, Igel C, Lauze F, Dam E, Nielsen M. Deep feature learning for knee cartilage segmentation using a triplanar convolutional neural network. *Med Image Comput Comput Assist Interv*. 2013;16(Pt 2):246–53. [https://doi.org/10.1007/978-3-642-40763-5\\_31](https://doi.org/10.1007/978-3-642-40763-5_31)
98. Liu F, Zhou Z, Samsonov A, Blankenbaker D, Larison W, Kanarek A, et al. Deep Learning Approach for Evaluating Knee MR Images: Achieving High Diagnostic Performance for Cartilage Lesion Detection. *Radiology*. 2018;289(1):160–9. <https://doi.org/10.1148/radiol.2018172986>
99. Astuto B, Flament I, K Namiri N, Shah R, Bharadwaj U, M Link T, et al. Automatic Deep Learning-assisted Detection and Grading of Abnormalities in Knee MRI Studies. *Radiol Artif Intell*. 2021;3(3):e200165. <https://doi.org/10.1148/ryai.2021200165>. Erratum in: *Radiol Artif Intell*. 2021;3(3):e219001. <https://doi.org/10.1148/ryai.2021219001>
100. Lee LS, Chan PK, Wen C, Fung WC, Cheung A, Chan VWK, et al. Artificial intelligence in diagnosis of knee osteoarthritis and prediction of arthroplasty outcomes: A review. *Arthroplasty*. 2022;4(1):16. <https://doi.org/10.1186/s42836-022-00118-7>
101. Wang S, Hou Y, Li X, Meng X, Zhang Y, Wang X. Practical implementation of artificial intelligence-based deep learning and cloud computing on the application of traditional medicine and western medicine in the diagnosis and treatment of rheumatoid arthritis. *Front Pharmacol*. 2021;12:765435.

102. Perni S, Prokopovich P. Feasibility and application of machine learning enabled fast screening of poly-beta-amino-esters for cartilage therapies. *Sci Rep.* 2022;12(1):14215. <https://doi.org/10.1038/s41598-022-18332-3>
103. Yang Y, Ye Z, Su Y, Zhao Q, Li X, Ouyang D. Deep learning for in vitro prediction of pharmaceutical formulations. *Acta Pharm Sin B.* 2019;9(1):177–185. <https://doi.org/10.1016/j.apsb.2018.09.010>
104. Robles-Bykbaev Y, Naya S, Díaz-Prado S, Calle-López D, Robles-Bykbaev V, Garzón L, et al. An artificial-vision- and statistical-learning-based method for studying the biodegradation of type I collagen scaffolds in bone regeneration systems. *PeerJ.* 2019;7:e7233. <https://doi.org/10.7717/peerj.7233>
105. Erisken C, Kalyon DM, Wang H. Functionally graded electrospun polycaprolactone and beta-tricalcium phosphate nanocomposites for tissue engineering applications. *Biomaterials.* 2008;29(30):4065–73.
106. Cutiongco MFA, Jensen BS, Reynolds PM, Gadegaard N. Predicting gene expression using morphological cell responses to nanopography. *Nat Commun.* 2020;11(1):1384. <https://doi.org/10.1038/s41467-020-15114-1>

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