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Artificial intelligence and machine learning | applications in musculoskeletal physiotherapy

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ABSTRACT

Introduction: Artificial intelligence (AI) is a field of mathematical engineering which has potential to enhance healthcare through new care delivery strategies, informed decision making and facilitation of patient engagement. Machine learning (ML) is a form of narrow artificial intelligence which can be used to automate decision making and make predictions based upon patient data.

Purpose: This review outlines key applications of supervised and unsupervised machine learning in musculoskeletal medicine; such as diagnostic imaging, patient measurement data, and clinical decision support. The current literature base is examined to identify areas where ML performs equal to or more accurately than human levels.

Implications: Potential is apparent for intelligent machines to enhance various areas of physiotherapy practice through automization of tasks which involve data analysis, classification and prediction. Changes to service provision through applications of ML, should encourage physiotherapists to increase their awareness of and experiences with emerging technologies. Data literacy should be a component of professional development plans to assist physiotherapists in the application of ML and the preparation of information technology systems to use these techniques.

1. Introduction

Artificial intelligence (AI) can enhance healthcare through advancement of care delivery, decision-making, and patient engagement (House of Lords, 2018). AI is the development of computer systems to solve problems associated with human intelligence (Fogel and Kvedar, 2018). "Narrow AI" (nAI)- intelligence in a specific area-is the currently used application of AI in society; and differs from theoretical "general AI" which simulates human-level intelligence across multiple domains (Franklin, 2007).

Machine learning (ML) is a form of nAI (Peek et al., 2015) where algorithms make predictions to interpret data and "learn", without static program instructions (Ayodele, 2010). There are two main forms of ML: supervised and unsupervised. Supervised ML is where algorithms are given training data, which is analysed for features important for classification and labelled. The model is then "trained" with this data before being tested with unlabelled data. For example, if the data are X-ray images, they are first labelled by a radiographer so the model can learn how to interpret. The model is then given unlabelled data and tested to give an output of interpretation. When the output is discrete (e.g. fracture present on X-ray vs no fracture) this is called "Classification" (prediction of a label). If the output is continuous (e.g. range of motion measurement) this is "Regression" (prediction of a quantity). Unsupervised ML is used to identify patterns without training. Common forms are cluster analysis (where data is grouped by patterns of characteristics) or association (where rules are discovered by which data is governed). Healthcare is suited for nAI, as complex datasets from electronic health records (EHR) provide challenging classification opportunities (Krittanawong, 2018). Benefits through pathway refinement and task automation can also reduce costs (Harwich and Laycock, 2018). This issue aims to outline current ML applications in the musculoskeletal field.

2. Supervised learning

2.1. Medical imaging

Fig. 1a illustrates supervised learning classification. It is essential that the ML model has sufficient labelled data from which to learn. Various forms of data are used in healthcare, and the abundance of diagnostic images collated makes them a prime target for classification (Berg, 2017). Table 1 shows the accuracy of supervised learning models across various areas of musculoskeletal medicine. For example, supervised learning can be used to teach ML models how to classify X-ray

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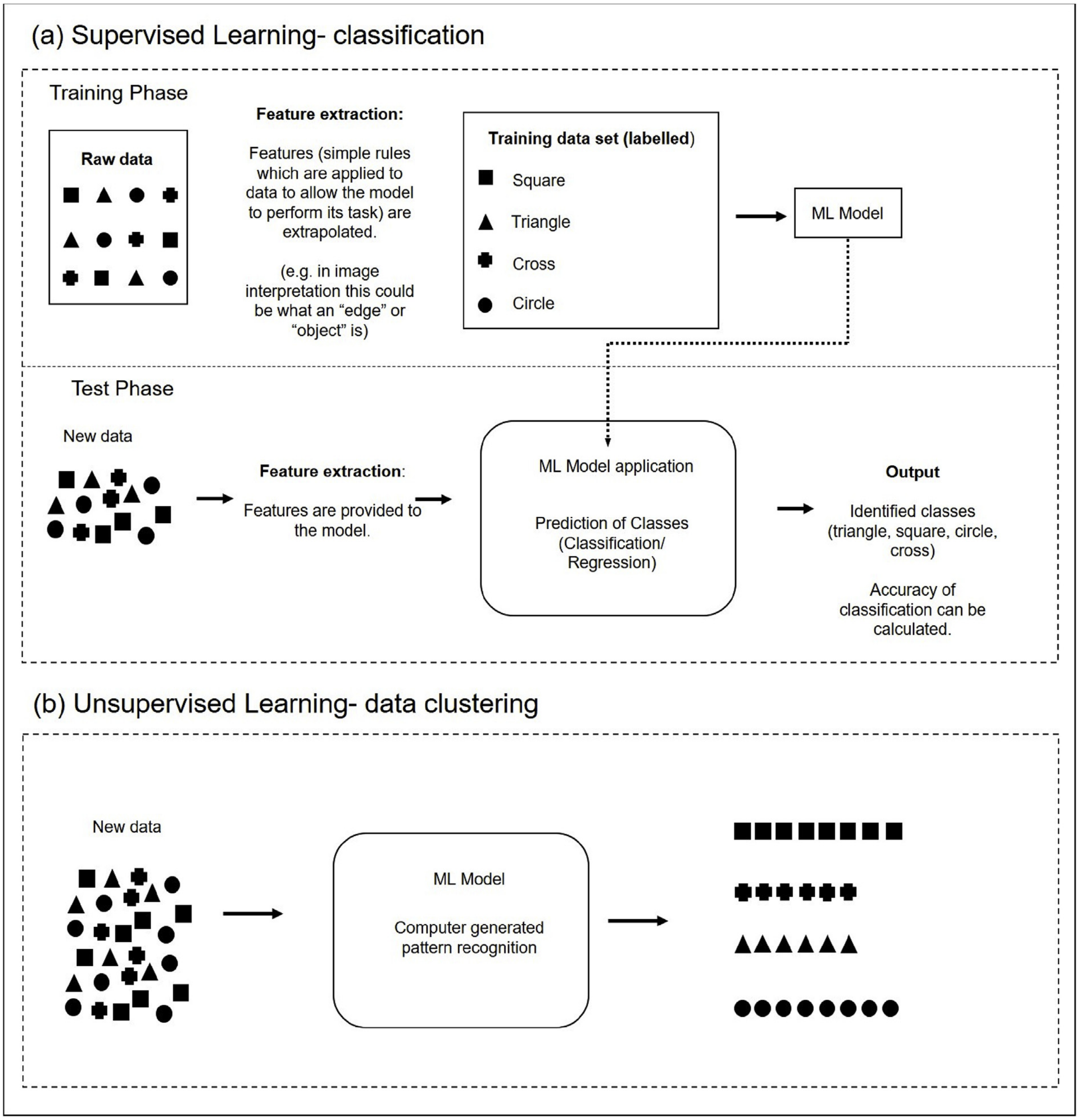

Fig. 1. Machine learning data processing examples (a) Supervised and (b) unsupervised learning.

and MRI images with accuracy equal to or greater than human experts (Jamaludin et al., 2017; Olczak et al., 2017); including whether pathophysiological changes (e.g. fracture or spinal degeneration) are present (Fig. 2). Similarly, models can be taught how to evaluate prospective MRI images of knee cartilage (Ashinsky et al., 2017), and predict the onset of arthritis 36 months before it is identifiable to human observers (75% accuracy). However, whilst automated image interpretation can be accurate, predictive and tireless; it does require large training datasets. This is particularly true when using complex neural network algorithms (systems based on mathematical models of the brain) like the above studies (Razzak et al. 2018). For example, Olczak et al. (2017) used 256,000 x-ray images to train their neural network to classify images. If annotated, anonymised image datasets could be made open-access, then superior automated diagnostic accuracy could attenuate service inequality; standardise image interpretation across healthcare institutions (Harwich and Laycock, 2018), and be an asset in settings without radiological expertise (Berg, 2017).

2.2. Pain

With long-standing pain prevalence of 30–50% in the UK (Fayaz et al., 2016), another application of supervised ML is in the classification of individuals to pain phenotypes based on brain MRI. Pain present without correlative tissue pathology, and reliance on self-reporting for subgrouping, makes identification of the neural correlates of pain an important challenge (Boissoneault et al., 2017). Lötsch and Ultsch (2018) summarise ML applications used in longstanding pain (not exclusively musculoskeletal); outlining the use of ML to classify subjects to a predicted pain phenotype. The review examines experimental pain (Chesler et al., 2002); fibromyalgia (Sevel et al., 2016); and low back pain (LBP) (Jiang et al., 2017); but provides no conclusions regarding effectiveness of ML classification.

ML methods show variable accuracy in discriminating between those with a pain condition and healthy individuals, based upon brain MRI (Boissoneault et al., 2017). Biomarkers (e.g. grey matter volume/ density or functional connectivity between regions) can be used for

Table 1
Accuracy of supervised machine learning techniques for musculoskeletal applications.

	Classification question	Data source	Classification label	Classification Accuracy [%]	Algorithm used
Olczak et al. (2017)	Is pathology present or not?	X-ray	Fracture (vs no fracture)	83	16 layer CNN
Jamaludin et al. (2017)		MRI	Pfirmann grade Disc narrowing Spondylolisthesis Central canal stenosis	70.4 75.4 95.4 94.7	CNN
Ashinsky et al. (2017)		MRI	Cartilage mapping	75	WND-CHRM
Bagarinao et al. (2014)	Is pain neuromapping phenotype identifiable with clinical diagnosis?	Structural MRI	CPP	73	SVM
Ung et al. (2012)			CLBP	76	SVM
Robinson et al. (2015)			FM	76	LR, MP, Bayes, SVM, j48 DT
Callan et al. (2014)		fMRI	CLBP	92	SLR
López-Solà et al. (2017)			FM	93	SVM, LR
Burns et al. (2018)	Can successful exercise performance be identified?	Inertial sensor	Accurate exercise performance	99.4 97.8 94.1	CNN k-NN SVM
Kianifar et al. (2017)	Can risk of injury be classified based upon movement quality?	Inertial sensor	Risk of injury with movement: “high” vs “low” “high” vs “moderate” “low” Accuracy of performance: “poor” vs “good” “poor” vs “moderate” vs “good”	95 72 90 60	10F-CV 10F-CV LOSO-CV LOSO-CV
Nijeweme-d'Hollosy et al. (2018)	Can CLBP subgroups be stratified accurately?	EHR	“Physiotherapy” vs “GP” vs “self-management”	71.05 71.05	DT BT

10F-CV- 10-fold cross-validation.
BT-boosted tree.
CLBP- chronic low back pain.
CNN- convolutional neural network.
CPP- chronic pelvic pain.
DT-decision tree.
EHR-electronic health records.
FM-fibromyalgia.
K-NN- k-nearest neighbour.
LOSO-CV- leave-one-subject-out cross-validation.
LR-logistical regression.
MP- multilayer perceptron.
SVM-support vector machine.
WND-CHRM- Weighted Neighbour Distances using a Compound Hierarchy of Algorithms Representing Morphology.

classification; acting as a surrogate to self-reporting (Mackey, 2013). With pain being heterogeneous, and a complex interplay of etiological, genetic and environmental factors (von Hehn et al., 2012); the implications of these studies are debatable. Furthermore, functional MRI shows greater accuracy but currently has limited use in the routine assessment of pain (Cowen et al., 2015). Table 1 outlines the accuracy of ML to identify brain phenotypes patterns for various pain conditions (e.g. LBP, fibromyalgia). Nevertheless, the potential for clinical application of ML-classified MRI for anatomical phenotyping of pain may develop in the future (Borsook and Becerra, 2007).

2.3. Wearable technology

Wearable technology offers a source of rich, epidemiological data through surveillance of physical behaviour; assistive in managing chronic disease (Phillips et al., 2018). Exercise adherence is often poor, despite being predictive of successful rehabilitation (Holden et al., 2014). Data collected via inertial sensors in wearable technology can be classified to identify whether users are accurately performing and adherent to exercise. Burns et al. (2018) tested performance accuracy in an asymptomatic population (n = 20) who performed a rotator-cuff exercise protocol (Kuhn et al., 2013) whilst wearing an Apple iWatch. Various methods of supervised learning were used to classify the accuracy of exercise (compared to an established dataset of “successful” performance); showing excellent accuracy across all algorithms. 99.4% classification accuracy was seen with a neural network, indicating promise for the use of wearable technologies and ML for exercise monitoring. As exercise performance has variable barriers to adherence (Jack et al., 2010), it is likely that measurement of performance through wearable technology alone, will be insufficient to optimise adherence. However, potential exists to use such data to identify and modify patient behaviour for clinical benefit.

2.4. Risk prediction

Frontal plane knee biomechanics are associated with knee injury risk prediction (Culvenor et al., 2014). Kianifar et al. (2017) used inertial sensor data to classify single-leg squat performance according to degree of knee valgus (n = 14, 140 images) and 3 expert raters' opinions of potential risk. They used supervised learning to classify between 3-classes (“poor”, “moderate” and “good”). The results found that accuracy was high during 2-class classification, but reduced by 30% with added complexity of 3-class classification. Supervised learning regression has also been applied to predict internal knee abduction moment based upon lower limb joint angles on video images during gait (Aljaaf et al., 2016). 3131 images were analysed, and various ensemble (multi-layer) learning strategies demonstrated good accuracy of estimating abduction moment. A neural network method, despite long training time, was deemed the best predictor of knee force. These studies show that visual and inertial sensor data can be analysed by ML to predict injury risk patterns associated with dynamic knee valgus. However, with injury risk being multifactorial, biomechanical

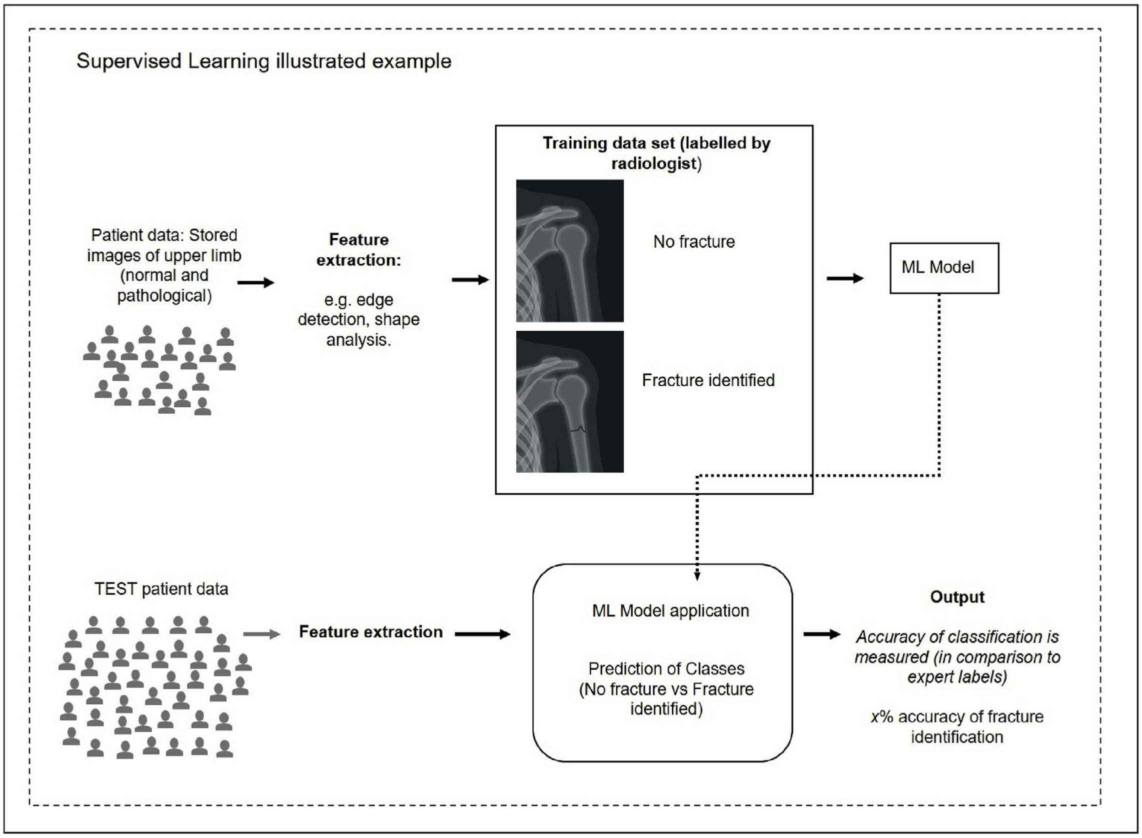

Fig. 2. Supervised learning illustrated example with fracture identification on x-ray.

data is likely only one part of injury prevention management (Murphy et al., 2003).

2.5. Decision support

Clinical decision support systems (CDSS) provide recommendations on diagnosis and treatment (Musen et al., 2014). Systems have been developed for LBP: for example the StartBack risk stratification tool which identifies prognostic indicators to classify individuals into risk groups (Hill et al., 2008). Nijeweme-d'Hollosy et al. (2016) developed a digital CDSS to stratify patients to self-management, GP attendance or self-referral to physiotherapy. An ontology and decision tree to classify subjects was developed according to 43 decision factors; such as general factors (e.g. occupation), 'psychosomatic' factors (e.g. depression, kinesiophobia); and serious pathology signs (i.e. red flags). Subsequently, supervised ML algorithms were applied to classify individuals using the CDSS (Nijeweme-d'Hollosy et al. 2018); finding all classified better than random allocation. This demonstrates the CDSS can successfully be used with ML to classify subjects, and further progress could make the combination more rigorous than by human decision-making. Comparably, human ability to delineate patients into low vs medium/high risk via StartBack is between 72.1 and 78.1% sensitivity and 42.91–75% specificity (Pagé et al., 2015). Thus, ML may provide more accurate allocation to services in the future, whilst increasing accessibility and speed of self-referral.

3. Unsupervised learning & data mining

There are few examples of unsupervised learning methods being used in the musculoskeletal field. The Chronic Pain Challenge (Navani and Li, 2016) predicts the risk of pain chronicity according to weighted values for health behaviours. It uses supervised and unsupervised methods, showing accurate prediction of pain (visual analogue scale) and Oswestry Disability Index; according to associated scores for depression, nutrition and physical activity. However, whilst this highlights the potential for ML to classify risk of chronicity based upon patient-reported data, the accuracy of unsupervised learning alone is not established.

Digitisation makes healthcare data accessible by computers (Bell, 2017; The Royal Society, 2017), with ML reliant on large datasets to accurately predict (Peek et al., 2015). Unsupervised learning is often applied within data-mining (the examination of large databases) in order to make new discoveries regarding risk or causation, where patterns are not obvious to clinicians (Obenshain, 2004). Such means have been used to identify symptoms predictive of chronic fatigue syndrome from diverse data sources (Watson et al., 2014). Ensuring data format, quality and security is essential to the adoption of ML, to prevent bias being placed into algorithms, and maintaining public trust in the use of health data (Hart, 2017; Harwich and Laycock, 2018; House of Lords, 2018). Health surveillance systems raise concerns over data privacy, however trends can be detected even with anonymised data (Obenshain, 2004). Physiotherapists should engage with digital transformation by becoming more data-literate, and professional development programmes should include basics of data science to prepare clinicians for future practice (House of Lords, 2018). Physiotherapists should become involved in the standardisation of diagnostic coding procedures to aid data usability (Williams et al., 2017); as well as assisting development of bespoke IT platforms, rather than reactive, plug-in alterations often seen in healthcare (Harwich and Laycock, 2018; Watson, 2016). This should facilitate interoperability within (and between) institutions to aid data sharing which is essential for unsupervised learning methods (Peek et al., 2015).

4. Conclusions

Supervised ML has potential to evolve physiotherapy practice, through super-human level diagnostics, decision making and measurement. For this, data sharing is paramount to train systems effectively. Unsupervised ML is unproven but may assist data-mining to identify patterns of association within patient populations. Physiotherapists should engage with technological innovation in practice, to guide its clinical application.

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References

Aljaaf, A.J., Hussain, A.J., Fergus, P., Przybyla, A., Barton, G.J., 2016. Evaluation of machine learning methods to predict knee loading from the movement of body segments. [Internet] In: IEEE International Joint Conference on Neural Networks (IJCNN), [cited 03 May 2018]. Available from: https://ieeexplore.ieee.org/document/7727882/.

Ashinsky, B.G., Bouhrara, M., Coletta, C.E., Lehallier, B., Urish, K.L., Lin, P.C., Spencer, R.G., 2017. Predicting early symptomatic osteoarthritis in the human knee using machine learning classification of magnetic resonance images from the osteoarthritis initiative. J. Orthop. Res. 35 (10), 2243–2250. https://doi.org/10.1002/jor.23519.

Ayodele, T.O., 2010. Machine Learning Overview: New Advances in Machine Learning. [Internet] InTech [cited 02 May 2018]. Available from: https://cdn.intechopen.com/pdfs-wm/10683.pdf.

Bagarinao, E., Johnson, K.A., Martucci, K.T., Ichesco, E., Farmer, M.A., Labus, J., et al., 2014. Preliminary structural MRI based brain classification of chronic pelvic pain: a MAPP network study. Pain 155 (12), 2502–2509. https://doi.org/10.1016/j.pain.2014.09.002.

Bell, J., 2017. Life Sciences Industrial Strategy- a Report to the Government from the Life Sciences Sector. [Internet] HM Government, United Kingdom [Cited 03 May 2018]. Available from: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/650447/LifeSciencesIndustrialStrategy_acc2.pdf.

Berg, H.E., 2017. Will intelligent machine learning revolutionize orthopedic imaging? Acta Orthop. 88 (6), 577. https://doi.org/10.1080/17453674.2017.1387732.

Boissoneault, J., Sevel, L., Letzen, J., Robinson, M., Staud, R., 2017. Biomarkers for musculoskeletal pain conditions: use of brain imaging and machine learning. Curr. Rheumatol. Rep. 19 (1), 1–9. https://doi.org/10.1007/s11926-017-0629-9.

Borsook, D., Becerra, L., 2007. Phenotyping central nervous system circuitry in chronic pain using functional MRI: considerations and potential implications in the clinic. Curr. Pain Headache Rep. 11 (3), 201–207. https://doi.org/10.1007/s11916-007-0191-7.

Burns, D., Leung, N., Hardisty, M., Whyne, C., Henry, P., McLachlin, S., 2018. Shoulder Physiotherapy Exercise Recognition: Machine Learning the Inertial Signals from a Smartwatch. [Internet] Cornell University Library (cited 02 May 2018]. Available from: https://arxiv.org/pdf/1802.01489.pdf.

Callan, D., Mills, L., Nott, C., England, R., England, S., 2014. A tool for classifying individuals with chronic back pain: using multivariate pattern analysis with functional magnetic resonance imaging data. PloS One 9 (6), e98007. https://doi.org/10.1371/journal.pone.0098007.

Chesler, E.J., Wilson, S.G., Lariviere, W.R., Rodriguez-Zas, S.L., Mogil, J.S., 2002. Identification and ranking of genetic and laboratory environment factors influencing a behavioral trait, thermal nociception, via computational analysis of a large data archive. Neurosci. Biobehav. Rev. 26, 907–923.

Cowen, R., Stasiowska, M.K., Laycock, H., Bantel, C., 2015. Assessing pain objectively: the use of physiological markers. Anaesthesia 70, 828–847. https://doi.org/10.1111/anae.13018.

Culvenor, A.G., Schache, A.G., Vicenzino, B., Pandy, M.G., Collins, N.J., Cook, J.L., Crossley, K.M., 2014. Are knee biomechanics different in those with and without patellofemoral osteoarthritis after anterior cruciate ligament reconstruction? Arthritis Care Res. 66 (10), 1566–1570.

Fayaz, A., Croft, P., Langford, R.M., Donaldson, L.J., Jones, G.T., 2016. Prevalence of chronic pain in the UK: a systematic review and meta-analysis of population studies. BMJ open 6 (6), e010364. https://doi.org/10.1136/bmjopen-2015-010364.

Fogel, A.L., Kvedar, J.C., 2018. Artificial intelligence powers digital medicine. npj Dig. Med. 1 (5), 1–4. https://doi.org/10.1038/s41746-017-0012-2.

Franklin, S.A., 2007. Foundational architecture for artificial general intelligence. In: Goertzel, B., Wang, P. (Eds.), Proceedings of the 2007 Conference on Advances in Artificial General Intelligence: Concepts, Architectures and Algorithms: Proceedings of the AGI Workshop 2006. IOS Press Amsterdam, The Netherlands, pp. 36–54.

Hart, R., 2017. If You're Not a White Male, Artificial Intelligence's Use in Healthcare Could Be Dangerous. Quartz. [Cited 03 May 2018]. Available from: https://qz.com/1023448/if-youre-not-a-white-male-artificial-intelligences-use-in-healthcare-could-be-dangerous/.

Harwich, E., Laycock, K., 2018. Thinking on its Own: AI in the NHS. [Internet] Reform [cited 02 May 2018]. Available from: http://www.reform.uk/wp-content/uploads/2018/01/AI-in-Healthcare-report.pdf.

Hill, J.C., Dunn, K.M., Lewis, M., Mullis, R., Main, C.J., Foster, N.E., Hay, E.M., 2008. A primary care back pain screening tool: identifying patient subgroups for initial treatment. Arthritis Care Res. 59 (5), 632–641. https://doi.org/10.1002/art.23563.

Holden, M.A., Haywood, K.L., Potia, T.A., Gee, M., McLean, S., 2014. Recommendations for exercise adherence measures in musculoskeletal settings: a systematic review and consensus meeting (protocol). Syst. Rev. 3 (10), 1–6.

House of Lords, 2018. House of Lords Select Committee on Artificial Intelligence. AI in the UK: ready, Willing and able? (Report of Session 2017–19). The Stationery Office, London. https://publications.parliament.uk/pa/ld201719/ldselect/ldai/100/100.pdf, Accessed date: 2 May 2018.

Jack, K., McLean, S.M., Moffett, J.K., Gardiner, E., 2010. Barriers to treatment adherence in physiotherapy outpatient clinics: a systematic review. Man. Ther. 15 (3), 220–228.

Jamaludin, A., Lootus, M., Kadir, T., Zisserman, A., Urban, J., Battié, M.C., Genodisc Consortium, 2017. ISSLS prize in bioengineering science 2017: automation of reading of radiological features from magnetic resonance images (MRIs) of the lumbar spine without human intervention is comparable with an expert radiologist. Eur. Spine J. 26 (5), 1374–1383. https://doi.org/10.1007/s00586-017-4956-3.

Jiang, N., Luk, K.D.K., Hu, Y., 2017. A machine learning based surface electromyography topography evaluation for prognostic prediction of functional restoration rehabilitation in chronic low back pain. Spine (Phila Pa 1976) 42, 1635–1642. https://doi.org/10.1097/BRS.0000000000002159.

Kianifar, R., Lee, A., Raina, S., Kulić, D., 2017. Automated assessment of dynamic knee valgus and risk of knee injury during the single leg squat. IEEE J. Trans. Eng. Health Med. 5 (2100213), 1–13. https://doi.org/10.1109/JTEHM.2017.2736559.

Krittanawong, C., 2018. The rise of artificial intelligence and the uncertain future for physicians. Eur. J. Intern. Med. 48 (1), e13–e14. https://doi.org/10.1016/j.ejim.2017.06.017.

Kuhn, J.E., Dunn, W.R., Sanders, R., An, Q., Baumgarten, K.M., Bishop, J.Y., Brophy, R.H., Carey, J.L., Holloway, B.G., Jones, G.L., et al., 2013. Effectiveness of physical therapy in treating atraumatic full thickness rotator cuff tears. A multicenter prospective cohort study. J. Shoulder Elbow Surg. 22 (10), 1371–1379.

López-Solà, M., Woo, C.W., Pujol, J., Deus, J., Harrison, B.J., Monfort, J., Wager, T.D., 2017. Towards a neurophysiological signature for fibromyalgia. Pain 158 (1), 34–47.

Lötsch, J., Ultsch, A., 2018. Machine learning in pain research. Pain 159 (4), 623–630. https://doi.org/10.1097/j.pain.0000000000001118.

Mackey, S.C., 2013. Central neuroimaging of pain. J. Pain: Off. J. Am. Pain Soc. 14 (4), 328–331. https://doi.org/10.1016/j.jpain.2013.01.001.

Murphy, D.F., Connolly, D.A., Beynnon, B.D., 2003. Risk factors for lower extremity injury: a review of the literature. Br. J. Sports Med. 37 (1), 13–29.

Musen, M.A., Middleton, B., Greenes, R.A., 2014. Clinical decision-support systems. In: Shortliffe, E., Cimino, J. (Eds.), Biomedical Informatics. Springer, London, pp. 643–674.

Navani, A., Li, G., 2016. Chronic Pain Challenge: a statistical machine-learning method for chronic pain assessment. J. Recent Adv. Pain 2 (3), 82–86.

Nijeweme-d'Hollosy, W.O., van Velsen, L.S., Soer, R., Hermens, H.J., 2016. Design of a web-based clinical decision support system for guiding patients with low back pain to the best next step in primary healthcare. In: Fred, A., Gambia, H. (Eds.), Proceedings of the 9th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2016). SCITEPRESS-Science and Technology Publications, Portugal, pp. 229–239.

Nijeweme-d'Hollosy, W.O., van Velsen, L.S., Poel, M., Groothuis-Oudshoorn, C.G., Soer, R., Hermens, H., 2018. Evaluation of three machine learning models for self-referral decision support on low back pain in primary care. Int. J. Med. Inf. 110, 31–41. https://doi.org/10.1016/j.ijmedinf.2017.11.010.

Obenshain, M.K., 2004. Application of data mining techniques to healthcare data. Infect. Contr. Hosp. Epidemiol. 25 (8), 690–695.

Olczak, J., Fahlberg, N., Maki, A., Razavian, A.S., Jilert, A., Stark, A., Sköldenberg, O., Gordon, M., 2017. Artificial intelligence for analyzing orthopedic trauma radiographs. Acta Orthop. 88 (6), 581–586. https://doi.org/10.1080/17453674.2017.1344459.

Pagé, I., Abboud, J., Laurencelle, L., Descarreaux, M., 2015. Chronic low back pain clinical outcomes present higher associations with the STarT Back Screening Tool than with physiologic measures: a 12-month cohort study. BMC Muscoskel. Disord. 16 (1), 201.

Peek, N., Combi, C., Marin, R., Bellazzi, R., 2015. Thirty years of artificial intelligence in medicine (AIME) conferences: a review of research themes. Artif. Intell. Med. 65 (1), 61–73. https://doi.org/10.1016/j.artmed.2015.07.003.

Phillips, S.M., Cadmus-Bertram, L., Rosenberg, D., Buman, M.P., Lynch, B.M., 2018. Wearable technology and physical activity in chronic disease: opportunities and challenges. Am. J. Prev. Med. 54 (1), 144–150.

Razzak, M.I., Naz, S., Zaib, A., 2018. Deep learning for medical image processing: overview, challenges and the future. In: Dey, N., Ashour, A., Borrab, s (Eds.), Classification in BioApps: Automation of Decision Making 2018. Springer, Cham, pp. 323–350.

Robinson, M.E., O'Shea, A.M., Craggs, J.G., Price, D.D., Letzen, J.E., Staud, R., 2015. Comparison of machine classification algorithms for fibromyalgia: neuroimages versus self-report. J. Pain: Off. J. Am. Pain Soc. 16 (5), 472–477. https://doi.org/10.1016/j.jpain.2015.02.002.

Sevel, L., Letzen, J., Boissoneault, J., O'Shea, A., Robinson, M., Staud, R., 2016. MRI based classification of chronic fatigue, fibromyalgia patients and healthy controls using machine learning algorithms: a comparison study. J. Pain 17, S60. https://doi.org/10.1016/j.jpain.2016.01.244.

The Royal Society, 2017. Machine Learning: the Power and Promise of Computers that Learn by Example. The Royal Society [Cited 03 May 2018]. Available from: https://royalsociety.org/~/media/policy/projects/machine-learning/publications/machine-learning-report.pdf.

Ung, H., Brown, J.E., Johnson, K.A., Younger, J., Hush, J., Mackey, S., 2012. Multivariate classification of structural MRI data detects chronic low back pain. Cerebr. Cortex 24 (4), 1037–1044. https://doi.org/10.1093/cercor/bhs378.

von Hehn, C.A., Baron, R., Woolf, C.J., 2012. Deconstructing the neuropathic pain phenotype to reveal neural mechanisms. Neuron 73 (4), 638–652. https://doi.org/10.1016/j.neuron.2012.02.008.

Watson, A.R., 2016. Impact of the digital age on transforming healthcare. In: Weaver, C.A., Ball, M.J., Kim, G.R., Kiel, J.M. (Eds.), Healthcare Information Management Systems. Springer, Cham, pp. 219–233.

Watson, S.P., Ruskin, A.S., Simonis, V., Jason, L.A., Sunnquist, M., Furst, J.D., 2014. Identifying defining aspects of chronic fatigue syndrome via unsupervised machine learning and feature selection. Int. J. Mach. Learn. Comput. 14 (2), 133.

Williams, R., Kontopantelis, E., Buchan, I., Peek, N., 2017. Clinical code set engineering for reusing EHR data for research: a review. J. Biomed. Inf. 70, 1–13. https://doi.org/10.1016/j.jbi.2017.04.010.