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ROLE OF ARTIFICIAL INTELLIGENCE IN DEEP LEARNING FOR ORTHOPEDIC SPECIFIC IMAGING AND CLINICAL DECISION

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ABSTRACT

tificial intelligence (AI) has made major advancements across several areas, including the medical fi eld.As these strategies advance, it is becoming usual for Artificial I to surpass physicians in specific settings.Machine learning is a subset of artificial intelligence that refers to a machine's abilit y to identify relationships in data without the need for predetermined criteria
(1).With more expertise and data, this relationship detection usually improves, allowing algorithms t o model connections that might be too complex for conventional statistical methods
(2).Branch of machine learning called "deep learning" deals with models built like artificial neural n etworks that mimic the neural connections found in the human brain (Fig. 1).
Aside from this quantity and quality of data, the correct feature selection is the main factor affecting the effectiveness of traditional machine learning algorithms.
(3)There isn't yet a widely recognized standard for the feature selection procedure.
Therefore, a thorough technique is still required to differentiate the technical and medical skills esse ntial when applying classical machine learning methods (2, 4).In contrast, deep learning has the benefit of doing analysis with input data, eliminating the necess ity for a feature selection phase. Without being limited by feature selection, this method enables the use of all available parameters required for the analysis (5).However, there is a barrier to entry with deep learning that requires data preparation before

training. Furthermore, having a high- graphics processing unit (GPU) is vital for conducting effective experiments, as the time and expenses associated with model training can sometime climb dramatically (6).

Because of its better performance, deep learning linked to computer vision, particularly convolutional neural networks (CNN), is used more often than traditional machine learning methods. The architecture of a CNN is made up of a convolutional layer, a pooling layer, and a fully connected layer. Dimension reduction and feature extraction are performed by the pooling and convolutional layers, respectively (7). The aforementioned layers produce a smaller feature map that is then fed into the completely connected layer, which yields the desired conclusion (Fig. 2). Because CNNs lack inherent interpretability (i.e., are black boxes), numerous other methods have been created to address this issue. (8)

Gradient-weighted Class Activation Mapping (Grad-CAM) is one such widely used computer vision algorithm that incorporates interpretability features. Grad-CAM creates images that emphasize crucial areas that are used as input for predictive models (9).Deep learning approaches to computer vision issues mostly involve classification, object identification, and segmentation. First, the input image is classified to determine which class it belongs to. Next, object detection determines whether a particular object is present or absent and uses a bounding box to indicate its position (10). Finally, segmentation provides the precise margin of an item in pixels. For instance, consider the task of using a knee MRI to identify a meniscus tear. The classification network is in charge of labeling "meniscus tear" versus "no meniscus tear" (Fig. 3a), the object detection network uses a bounding box to locate and classify the meniscus tear (Fig. 3b), and the segmentation network is able to show the precise location and degree of the meniscus tear (Fig. 3c). With this editorial, we will introduce the presence of fracture (accuracy = 1.00), and the network's performance on identifying the kind of fracture was comparable to that of an orthopedic surgeon who specializes in the shoulder (accuracy 65–86%). (11)

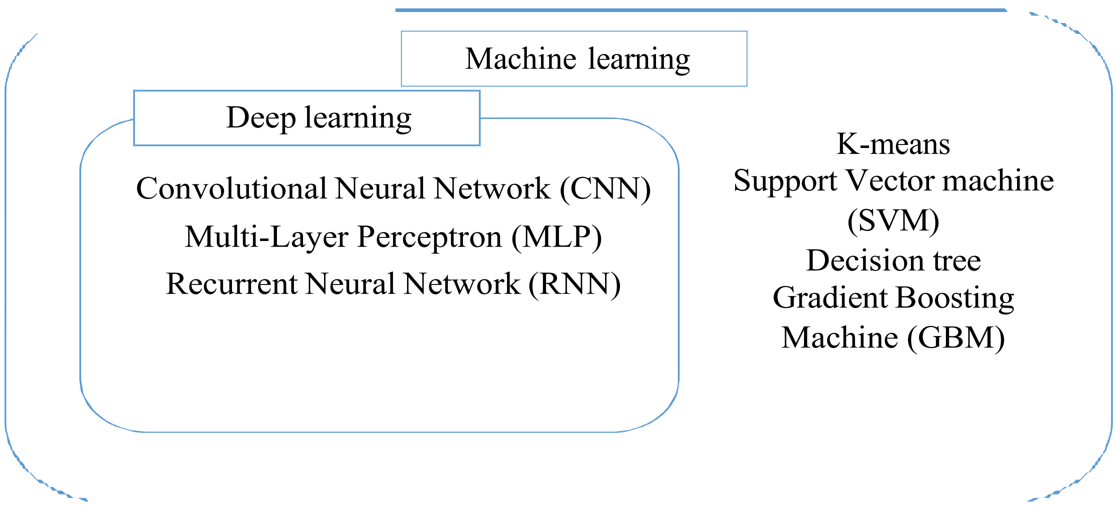


Fig. 1 Venn diagram demonstrating the relationships and typical examples of machine learning and deep learning. Deep learning is a field of machine learning that refers to a model with an artificial neural network structure that mimics the human brain's neural connections the deep learning technologies used in orthopedic medical imaging in relation to the three strategies above and provide examples of how they are used in addition to the associated algorithms/neural networks. This simplified workflow can be extended to other more complex imaging tasks. It is meant to be a framework to think about computer vision problems, though is not meant to be comprehensive.

Classification

One of the most well-known and well-recognized classification neural networks is Res Net. A classification network is often used to evaluate the existence of abnormalities, categorize their kind, or assess their severity. The easiest among the three strategies is the labeling process of the classification network, as only the class of each image need to be labeled. For example, Chung et al. utilized 1,891 simple anteroposterior shoulder radiographs to determine the presence of proximal humerus fracture (yes/no) and the type of fracture. The deep learning model flawlessly identified (12)

Object detection

The most widely known object detection neural network is YOLO (You Only Look Once). YOLO annotates a target object by a bounding box and reports the category the target object belongs to. As inferred by its name, the YOLO network works rapidly, allowing real-time analysis of images and videos. Due to this advantage, it is mainly used to assess surgical videos in medical fields, such as in the real-time detection of surgical instruments, anatomical structures, and the stage of surgery. However, compared to the classification network, YOLO network takes a relatively longer time to prepare (label) the data as the class of the objects needs to be annotated (13). For example, Hossain et al. developed a deep learning model that detects surgical instruments in real-time from 16 total knee arthroplasty images recorded at 25 fps. This deep learning model classified 31 surgical instruments at 87.6% mean average precision (MAP). Real-time analysis of surgical videos can be further developed into automated intraoperative assistance and have great potential such as being an automated feedback system for trainees (14).

Segmentation

U-net is one of the most powerful and established segmentation neural networks. A segmentation network reports the exact pixel-wise probability of the presence of the tar- get object. Due to this advantage, it is mainly used for precise tasks—such as identifying the contour of organs or the extent of tumors. However, to train the network, pixel-wise annotation of train images is required, which can consume **(15)**

Fig. 2 Architecture of a Convo- lutional Neural Network (CNN). CNN is multi-layer network constituted of a 1) convolutional layer, pooling layer, and fully connected layer. Convolutional and pooling layers are used for feature extraction and dimension reduction, respectively, while fully connected layers receive a reduced feature map and provide the outcome of interest

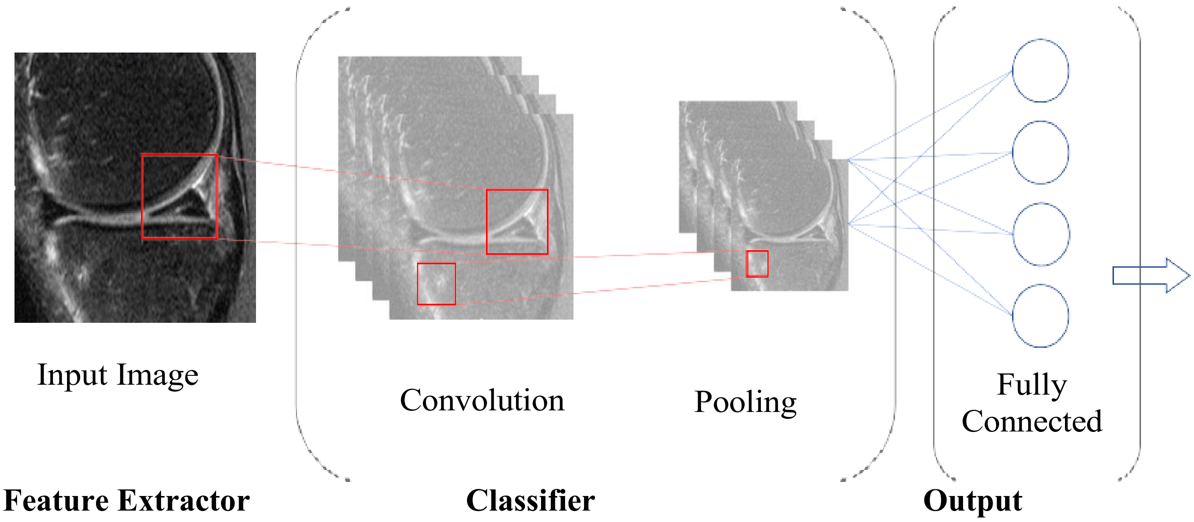
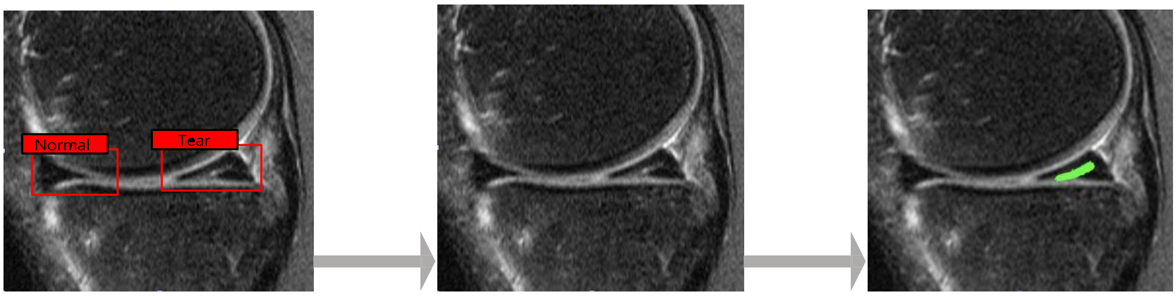


Fig. 3 Three approaches to solving computer vision problems with deep learning **a** classification, **b** object detection, and **c** segmentation. Classification is used to identify the appropriate class the input image corresponds to. Object detection identifies the presence or absence of a specific object and marks its location with a bounding box (red). Segmentation reports the exact pixel-wide margin of an

object (green)
Classification Object Detection (b) Segmentation Meniscus tear Present



significant resources, and is both humanly and computationally expensive. For example, Norman et al. developed a model for segmentation of cartilage and meniscus from 638 knee MR imaging. The volume and thickness of cartilage were automatically assessed by the network with a good performance (Dice coefficients 0.770–0.878 in cartilage and 0.809, 0.753 for lateral and medial meniscus, respectively). In another example, Hemke et al. utilized a segmentation network to analyze body composition. Pelvic muscles, fat, and bone was segmented from a pelvic CT image with an excellent performance (Dice score 0.91–0.97).

Combination strategies
These three strategies are commonly used to address computer vision problems and achieve deep learning solutions in the orthopedic field. Although introduced separately, they can also be used in combination with one another and often are. For example, Liu et al. used a segmentation net- work from a knee MR image to identify the cartilage region. The cartilage regions were cropped into a small square patch for the classification network to detect the cartilage lesion. Identification of cartilage area allowed the classification network to focus on cartilage area, yielding better performances (16).

Conclusion
In summary, there are three common strategies to assess medical images using deep learning: classification, object detection, and segmentation, and appropriate deep learning algorithms/networks should be chosen in response to the purpose of the study. Currently, despite the significant implications deep learning technology can have on orthopedics given our dependence on medical imaging for diagnosis and management, deep learning research in orthopedic surgery remains relatively sparse. Therefore, while caution should be exercised in adoption of new technology, we must prioritize deep learning as a tool to maintain the leadership role of orthopedic surgery in the musculoskeletal space.

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Declarations

Ethical approval: The study was exempt from institutional approval due to lack of data/biological material in accordance with ethical standards.

References
1. Baghbani S, Mehrabi Y, Movahedinia M, Babaeinejad E, Joshaghanian M, Amiri S, et al. The revolutionary impact of artificial intelligence in orthopedics: comprehensive review of current benefits and challenges. Journal of robotic surgery. 2025;19(1):511.
2. Collado-Mesa F, Alvarez E, Arheart K. The role of artificial intelligence in diagnostic radiology: a survey at a single radiology residency training program. Journal of the American College of

Radiology. 2018;15(12):1753-7.

3. Sharma S. Artificial intelligence for fracture diagnosis in orthopedic X-rays: current developments and future potential. SICOT-J. 2023;9:21.
4. Farhadi F, Barnes MR, Sugito HR, Sin JM, Henderson ER, Levy JJ. Applications of artificial intelligence in orthopaedic surgery. Frontiers in medical technology. 2022;4:995526.
5. Fazal MI, Patel ME, Tye J, Gupta Y. The past, present and future role of artificial intelligence in imaging. European journal of radiology. 2018;105:246-50.
6. Hardy M, Harvey H. Artificial intelligence in diagnostic imaging: impact on the radiography profession. The British journal of radiology. 2020;93(1108):20190840.
7. Hussain A, Fareed A, Taseen S. Bone fracture detection—Can artificial intelligence replace doctors in orthopedic radiography analysis? Frontiers in artificial intelligence. 2023;6:1223909.
8. Tariq A, Gill AY, Hussain HK. Evaluating the potential of artificial intelligence in orthopedic surgery for value-based healthcare. International Journal of Multidisciplinary Sciences and Arts. 2023;2(2):27-35.
9. Innocenti B, Radyul Y, Bori E. The use of artificial intelligence in orthopedics: Applications and limitations of machine learning in diagnosis and prediction. Applied Sciences. 2022;12(21):10775.
10. Kahn Jr CE. Artificial intelligence in radiology: decision support systems. Radiographics. 1994;14(4):849-61.
11. Lisacek-Kiosoglous AB, Powling AS, Fontalis A, Gabr A, Mazomenos E, Haddad FS. Artificial intelligence in orthopaedic surgery: exploring its applications, limitations, and future direction. Bone & joint research. 2023;12(7):447-54.
12. Mun SK, Wong KH, Lo S-CB, Li Y, Bayarsaikhan S. Artificial intelligence for the future radiology diagnostic service. Frontiers in molecular biosciences. 2021;7:614258.
13. Najjar R. Redefining radiology: a review of artificial intelligence integration in medical imaging. Diagnostics. 2023;13(17):2760.
14. Panchmatia JR, Visenio MR, Panch T. The role of artificial intelligence in orthopaedic surgery. British Journal of Hospital Medicine. 2018;79(12):676-81.
15. Rezazade Mehrizi MH, van Ooijen P, Homan M. Applications of artificial intelligence (AI) in diagnostic radiology: a technography study. European radiology. 2021;31(4):1805-11.
16. Song J, Wang G-C, Wang S-C, He C-R, Zhang Y-Z, Chen X, et al. Artificial intelligence in orthopedics: fundamentals, current applications, and future perspectives. Military Medical Research. 2025;12(1):42.