

Advanced Medical Imaging Techniques Using Artificial Intelligence

Simo Saarakkala

Professor, University of Oulu, Finland

Abstract

Artificial intelligence is increasingly transforming medical imaging by enabling advanced analysis of radiological and biomedical images, automated pattern recognition, image segmentation, disease detection, and clinical decision support. Conventional medical imaging generates complex visual information that requires considerable expertise and time for interpretation. Artificial intelligence, particularly machine learning and deep learning, provides computational approaches for extracting clinically relevant patterns from large imaging datasets. This study examines advanced medical imaging techniques using artificial intelligence, focusing on image acquisition, preprocessing, segmentation, classification, detection, reconstruction, and predictive analysis. A qualitative descriptive and conceptual research design was adopted using secondary academic literature. The analysis indicates that AI can support major imaging modalities, including magnetic resonance imaging, computed tomography, ultrasound, digital radiography, mammography, and nuclear imaging.

Deep-learning architectures, particularly convolutional neural networks, can support automated feature extraction and image interpretation. AI-assisted imaging can contribute to earlier disease detection, improved diagnostic consistency, workflow optimization, and quantitative assessment. However, challenges involving image quality, dataset diversity, algorithmic bias, interpretability, data privacy, cybersecurity, interoperability, clinical validation, and regulatory requirements remain significant. The study concludes that AI-enabled medical imaging can strengthen diagnostic capabilities when implemented with clinically validated models, high-quality datasets, appropriate human oversight, and secure healthcare infrastructures. Future research should emphasize multimodal imaging, explainable AI, three-dimensional analysis, federated learning, personalized imaging, real-time image interpretation, and clinically integrated intelligent imaging systems.

Keywords: Artificial Intelligence, Medical Imaging, Deep Learning, Machine Learning, Image Analysis, Medical Diagnosis, Computer Vision, Radiology, Biomedical Imaging, Clinical Decision Support

1. Introduction

Medical imaging is a fundamental component of modern healthcare because it enables clinicians to visualize anatomical structures, physiological processes, and pathological abnormalities. Imaging technologies such as computed tomography, magnetic resonance imaging, ultrasound, digital radiography, mammography, and nuclear imaging generate extensive visual information that supports diagnosis and treatment planning. As imaging technologies become increasingly sophisticated, the

volume and complexity of medical images have also expanded. This development has created a growing need for computational techniques capable of efficiently analyzing large quantities of imaging data.

Artificial intelligence has emerged as an important technological approach for addressing these requirements. AI systems can analyze medical images using machine-learning and deep-learning algorithms capable of identifying patterns that may be difficult to recognize through conventional computational methods. These technologies can support image classification, object detection, segmentation, reconstruction, and quantitative measurement. Litjens et al. (2017) identified deep learning as a major development in medical image analysis, demonstrating its expanding relevance across multiple imaging applications.

Deep learning has particularly influenced medical image analysis because it can automatically learn hierarchical representations from imaging datasets. Convolutional neural networks have been extensively applied to image classification and detection tasks. Unlike conventional image-analysis methods that may require manually engineered features, deep-learning approaches can learn relevant features directly from image data. This capability has contributed to the development of increasingly sophisticated AI-based imaging systems.

Medical image preprocessing represents an important stage in AI-enabled imaging. Images may contain noise, artifacts, inconsistent intensity values, motion effects, or other technical variations. Preprocessing techniques can improve image quality and standardize information before computational analysis. Appropriate preprocessing can improve model performance, although excessive transformation may remove clinically relevant characteristics. Therefore, preprocessing methods should be carefully selected according to imaging modality and clinical application.

Image segmentation is another major application of artificial intelligence. Segmentation involves identifying specific anatomical structures, organs, tissues, lesions, or pathological regions within an image. Accurate segmentation can support disease measurement, treatment planning, surgical navigation, and quantitative analysis. AI-based segmentation models can automate or accelerate this process, reducing the manual workload associated with conventional approaches.

Image classification enables AI systems to categorize images according to predefined clinical conditions. For example, classification models can differentiate between normal and abnormal images or identify particular disease categories. Automated classification can support screening programs and diagnostic workflows. However, classification outputs must be interpreted within the broader clinical context because image characteristics alone may not capture all relevant patient information.

Object detection provides another imaging capability by identifying and localizing specific structures or abnormalities. Detection systems can highlight suspicious regions and potentially support radiologists in reviewing large imaging datasets. This can be particularly valuable in high-volume clinical environments where healthcare professionals must evaluate substantial numbers of images within limited periods.

2. Objectives of the Study

Primary Objective

The primary objective of this study is to examine advanced medical imaging techniques using artificial intelligence by analyzing AI applications in image preprocessing, segmentation, classification, detection,

reconstruction, quantitative analysis, and clinical decision support. The study seeks to understand how AI can enhance imaging efficiency, diagnostic support, disease assessment, workflow management, and personalized healthcare while maintaining accuracy, transparency, privacy, safety, and clinical reliability.

2.1 Examination of AI-Based Medical Imaging Techniques

The first objective is to examine major AI-based medical imaging techniques, including deep-learning classification, automated segmentation, abnormality detection, image reconstruction, quantitative imaging, and multimodal image analysis. The study evaluates how these techniques can process complex medical images and support the identification, measurement, and characterization of anatomical structures and pathological conditions across different imaging modalities.

2.2 Assessment of Clinical Imaging Applications

The second objective is to assess the clinical applications of AI-enabled imaging across radiology, oncology, pathology, cardiovascular imaging, neurological imaging, and screening. The study examines how AI can support disease detection, diagnostic interpretation, treatment planning, longitudinal monitoring, and clinical decision support while considering integration with professional expertise and established healthcare workflows.

2.3 Identification of Implementation Requirements

The third objective is to identify important requirements affecting AI-based medical imaging, including image quality, dataset diversity, algorithmic fairness, interpretability, privacy, cybersecurity, interoperability, clinical validation, and regulatory compliance. The study examines how these factors influence reliable implementation and emphasizes the importance of clinically validated, secure, transparent, generalizable, and human-centered AI imaging systems.

3. Review of Literature

3.1 Artificial Intelligence in Medical Image Analysis

Artificial intelligence has significantly expanded medical image-analysis capabilities by enabling automated feature extraction, classification, segmentation, and detection. Litjens et al. (2017) reviewed deep-learning applications across multiple medical imaging domains and identified substantial progress in automated image analysis. Deep-learning approaches can process complex visual information and identify patterns associated with disease, although their performance depends strongly on dataset quality and appropriate validation.

Convolutional neural networks have become widely associated with medical image classification and detection because they can learn spatial features from images. Esteva et al. (2017) demonstrated the potential of deep neural networks for medical image classification in dermatology. Such findings illustrate the broader potential of AI for image-based diagnosis, while also highlighting the importance of representative datasets, appropriate clinical validation, and integration with professional clinical interpretation.

3.2 AI-Based Segmentation, Reconstruction, and Quantitative Imaging

Automated segmentation is an important area of medical imaging research because it enables identification and measurement of anatomical structures and pathological regions. AI-based segmentation can reduce manual workload and support quantitative assessment. U-Net-based architectures have become particularly influential in biomedical image segmentation because they can combine contextual information with spatial precision.

AI is also increasingly investigated for image reconstruction. Deep-learning reconstruction methods can potentially improve image quality from limited or noisy measurements. In MRI and CT, reconstruction techniques may contribute to faster acquisition or improved image quality. However, reconstruction algorithms must be carefully evaluated to ensure that computationally generated image characteristics do not obscure or distort clinically relevant information.

3.3 Clinical Integration and Explainable Imaging AI

AI-based medical imaging systems can provide decision-support information such as classifications, probability estimates, highlighted abnormalities, and quantitative measurements. Topol (2019) emphasized that AI can support high-performance medicine when combined appropriately with human expertise. Imaging AI should therefore be incorporated into clinical workflows rather than treated as an isolated automated diagnostic mechanism.

Explainability has become increasingly important because clinicians may need to understand why an imaging system produces a particular prediction. Amann et al. (2020) emphasized the importance of explainability in healthcare AI. Effective explanations can support transparency and trust, but their clinical usefulness must be evaluated carefully. External validation and monitoring are also necessary to ensure that imaging AI remains reliable across institutions and patient populations.

4. Research Methodology

4.1 Research Design

This study adopted a qualitative descriptive and conceptual research design to examine advanced medical imaging techniques using artificial intelligence. Secondary academic literature concerning medical imaging, artificial intelligence, machine learning, deep learning, image segmentation, classification, reconstruction, radiology, pathology, and clinical decision support was reviewed.

The conceptual framework considered image acquisition, preprocessing, AI-based analysis, clinical interpretation, and decision support as interconnected stages. These components were evaluated according to diagnostic relevance, computational performance, accuracy, interpretability, generalizability, privacy, safety, and clinical usability. The framework provides a structured basis for understanding AI integration within modern medical imaging.

4.2 Data Collection

Secondary information was collected from peer-reviewed journal articles, scholarly books, and established academic publications addressing artificial intelligence and medical imaging. Literature concerning CT, MRI, ultrasound, mammography, radiography, nuclear imaging, digital pathology, deep learning, image segmentation, image reconstruction, and computer-aided diagnosis was included.

The literature was categorized according to technological technique and imaging application. Technique categories included classification, detection, segmentation, reconstruction, quantitative analysis, and multimodal integration. Application categories included diagnosis, screening, disease monitoring, treatment planning, and clinical decision support. Literature addressing explainability, privacy, cybersecurity, interoperability, bias, and validation was also considered.

4.3 Data Analysis

The collected literature was analyzed using thematic analysis. Major themes included AI-based image interpretation, automated segmentation, disease detection, image reconstruction, quantitative imaging, clinical decision support, explainability, dataset quality, fairness, privacy, and clinical validation. Each theme was examined according to technological contribution and clinical relevance.

A conceptual synthesis was developed to describe how AI can transform medical images into clinically useful information. Images are acquired and prepared, AI algorithms analyze relevant patterns, outputs are validated and interpreted, and clinically appropriate information is presented to healthcare professionals. Human expertise remains important for integrating AI-generated information with patient-specific clinical evidence.

5. Analysis

5.1 Advanced AI-Based Medical Imaging Techniques

AI supports multiple stages of medical image analysis.

Table 1: AI Techniques and Medical Imaging Applications

AI Technique	Imaging Function	Clinical Contribution
Image Classification	Categorization of images	Diagnostic support
Image Segmentation	Identification of structures	Quantitative assessment
Object Detection	Localization of abnormalities	Screening support
Deep Learning	Automated feature extraction	Pattern recognition
Image Reconstruction	Enhancement of image information	Improved image quality
Quantitative Imaging	Numerical feature extraction	Disease assessment
Multimodal AI	Integration of imaging sources	Comprehensive analysis
Predictive Modeling	Outcome estimation	Clinical decision support

The analysis indicates that AI can contribute across the complete medical imaging workflow. Classification can support diagnostic categorization, segmentation can facilitate measurement, detection can identify suspicious regions, and reconstruction can improve imaging information. Integration of these capabilities can potentially increase efficiency while providing additional quantitative evidence for clinical interpretation.

5.2 Imaging Modalities and Healthcare Applications

AI applications differ according to imaging modality and clinical purpose.

Table 2: AI Applications Across Medical Imaging Modalities

Imaging Modality	AI Application	Healthcare Use
MRI	Segmentation and classification	Neurological and tissue assessment
CT	Detection and reconstruction	Disease and lesion analysis
Ultrasound	Interpretation and measurement	Real-time clinical assessment
Mammography	Abnormality detection	Breast screening
Digital X-Ray	Classification and detection	Diagnostic support
PET	Quantitative analysis	Functional assessment
Digital Pathology	Tissue classification	Pathological diagnosis
3D Imaging	Structural analysis	Surgical and treatment planning

The analysis demonstrates that AI has broad applicability across imaging modalities. However, imaging systems differ in acquisition methods, noise characteristics, resolution, and clinical interpretation. Consequently, AI models must be appropriately designed and validated for specific modalities and clinical tasks rather than assuming that one model can reliably operate across all imaging environments.

6. Discussion

AI-based medical imaging represents a significant development in healthcare because it can transform large and complex image datasets into structured clinical information. Automated classification, detection, and segmentation can support healthcare professionals by identifying potentially relevant patterns and reducing repetitive analytical workloads. AI can therefore complement conventional imaging interpretation while potentially improving efficiency and consistency.

Deep learning has become particularly important because it can automatically learn image features from large datasets. Convolutional neural networks and related architectures have demonstrated strong capabilities across different imaging tasks. However, model performance can depend heavily on the quality and diversity of training data. High accuracy within a development dataset does not necessarily guarantee reliable performance in different clinical environments.

Medical image segmentation provides important opportunities for quantitative healthcare. Automated identification of organs, lesions, tumors, and other structures can support measurements that may be difficult to obtain efficiently through manual procedures. Quantitative information can assist treatment planning and disease monitoring. However, segmentation errors can affect subsequent measurements and therefore require careful validation.

AI-based reconstruction can potentially improve the efficiency of medical imaging. In modalities such as MRI and CT, reconstruction approaches may help address limitations involving acquisition time, noise, or incomplete measurements. Faster imaging could improve workflow efficiency and patient comfort. Nevertheless, reconstructed images must preserve clinically meaningful information, and rigorous testing is necessary to ensure that AI-generated features do not introduce misleading characteristics..

7. Challenges

7.1 Image Quality and Dataset Diversity

Medical images can vary substantially because of differences in scanners, acquisition protocols, resolution, noise, contrast, patient characteristics, and clinical environments. Such variability can affect AI performance and make it difficult to develop universally reliable models. Poor-quality images may further reduce prediction accuracy and increase the possibility of incorrect classifications, detections, or segmentations.

Dataset diversity is therefore essential for generalizable medical imaging AI. Training data should represent relevant clinical populations, disease presentations, imaging equipment, and acquisition conditions. External validation can help determine whether models perform consistently outside their development environment. Multi-institutional datasets can further improve robustness and reduce dependence on a single clinical setting.

7.2 Interpretability and Clinical Trust

Many advanced AI imaging models operate as complex computational systems whose internal decision processes may be difficult to understand. Clinicians may require evidence concerning the image regions or characteristics responsible for an AI prediction. Limited interpretability can reduce confidence and make it difficult to identify whether an output is clinically reasonable.

Explainable AI techniques can provide visual or feature-based information concerning model predictions. However, explanations must be clinically meaningful rather than merely technically informative. Appropriate visualization, uncertainty communication, and comparison with clinical evidence can support responsible interpretation. Human oversight remains essential when AI-generated imaging results influence diagnosis or treatment.

7.3 Privacy, Cybersecurity, and Interoperability

Medical images contain sensitive information and may be stored across hospital systems, research databases, and cloud platforms. Unauthorized access or insecure transmission can create significant privacy risks. Secure storage, encryption, authentication, access management, de-identification, and controlled information sharing are necessary to protect imaging data.

Interoperability is another challenge because imaging systems and healthcare information platforms may use different standards and technical architectures. Lack of interoperability can prevent AI systems from accessing relevant information or returning results efficiently. Standardized data formats, communication protocols, and integration mechanisms can support smoother implementation of AI-enabled medical imaging.

7.4 Clinical Validation and Regulatory Requirements

Strong performance in experimental datasets does not automatically demonstrate clinical effectiveness. AI imaging systems require appropriate validation to determine whether they provide reliable results across patient populations and clinical environments. Prospective studies can provide stronger evidence concerning safety, usability, workflow effects, and patient outcomes.

Regulatory requirements can further influence AI imaging development. Systems may need to demonstrate appropriate performance, safety, risk management, and clinical utility. Adaptive models can create additional challenges because their behavior may change following updates or exposure to new data. Continuous monitoring and appropriate documentation are therefore important for maintaining reliability and regulatory compliance.

8. Future Research

Future research should emphasize multimodal and three-dimensional AI imaging systems capable of integrating information across different imaging modalities. Explainable AI should be further developed to provide clinically meaningful interpretations of automated predictions. Research should also investigate real-time image analysis, AI-assisted reconstruction, personalized imaging biomarkers, and intelligent systems that can adapt to patient-specific imaging characteristics.

Further studies should prioritize large, diverse, multi-institutional datasets and prospective clinical validation. Federated learning and privacy-preserving approaches could support collaborative model development while limiting centralized exposure of sensitive imaging data. Research should also examine model drift, fairness, cybersecurity, interoperability, workflow integration, and patient outcomes. These efforts can strengthen the clinical reliability and responsible adoption of AI-based medical imaging.

9. Conclusion

Artificial intelligence is transforming medical imaging by providing advanced capabilities for image classification, segmentation, detection, reconstruction, quantitative analysis, and clinical decision support. These technologies can process complex imaging information and assist healthcare professionals in identifying abnormalities and evaluating disease characteristics. Their integration provides opportunities for improving imaging efficiency, consistency, and diagnostic support.

Deep-learning methods have demonstrated particular potential for medical image analysis because they can learn complex visual representations from large datasets. AI can be applied across MRI, CT, ultrasound, mammography, digital radiography, nuclear imaging, and digital pathology. However, each modality presents different technical and clinical requirements, making modality-specific development and validation necessary.

The effectiveness of medical imaging AI depends heavily on data quality and clinical validation. Differences in scanners, imaging protocols, patient populations, and healthcare environments can influence model performance. Diverse datasets, external validation, prospective studies, and continuous monitoring are therefore essential. AI systems should also be evaluated according to clinical usefulness rather than technical accuracy alone.

Explainability, privacy, cybersecurity, interoperability, and fairness must be considered throughout AI imaging development. Clinicians need understandable information concerning AI-generated outputs, while healthcare organizations require secure and interoperable infrastructures. Responsible governance can help protect patient information and support appropriate use of AI within clinical environments.

Overall, advanced medical imaging techniques using artificial intelligence have substantial potential to support future healthcare innovation. Their greatest value can be achieved when AI systems complement professional expertise rather than operate independently. Future development should prioritize clinically validated, explainable, secure, equitable, interoperable, and patient-centered imaging technologies. Such an approach can strengthen diagnostic capabilities while supporting safer and more efficient healthcare delivery.

References

1. Doi, K. (2007). Computer-aided diagnosis in medical imaging: Historical review, current status and future potential. *Computerized Medical Imaging and Graphics*, 31(4–5), 198–211. <https://doi.org/10.1016/j.compmedimag.2007.02.002>
2. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., van der Laak, J. A. W. M., van Ginneken, B., & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis*, 42, 60–88. <https://doi.org/10.1016/j.media.2017.07.005>
3. Shen, D., Wu, G., & Suk, H.-I. (2017). Deep learning in medical image analysis. *Annual Review of Biomedical Engineering*, 19, 221–248. <https://doi.org/10.1146/annurev-bioeng-071516-044442>
4. Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., Venugopalan, S., Widner, K., Madams, T., Cuadros, J., Kim, R., Raman, R., Nelson, P. C., Mega, J. L., & Webster, D. R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *JAMA*, 316(22), 2402–2410. <https://doi.org/10.1001/jama.2016.17216>
5. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, 542, 115–118. <https://doi.org/10.1038/nature21056>
6. Rajkomar, A., Oren, E., Chen, K., Dai, A. M., Hajaj, N., Hardt, M., Liu, P. J., Liu, X., Marcus, J., Sun, M., Sundberg, P., Yee, H., Zhang, K., Zhang, Y., Flores, G., Duggan, G. E., Irvine, J., Le, Q., Litsch, K., ... Dean, J. (2018). Scalable and accurate deep learning with electronic health records. *npj Digital Medicine*, 1, Article 18. <https://doi.org/10.1038/s41746-018-0029-1>
7. Kermany, D. S., Goldbaum, M., Cai, W., Valentim, C. C. S., Liang, H., Baxter, S. L., McKeown, A., Yang, G., Wu, X., Yan, F., Dong, J., Prasadha, M. K., Pei, J., Ting, M. Y. L., Zhu, J., Li, C., Hewett, S., Dong, J., Ziyar, I., ... Zhang, K. (2018). Identifying medical diagnoses and treatable diseases by image-based deep learning. *Cell*, 172(5), 1122–1131.e9. <https://doi.org/10.1016/j.cell.2018.02.010>
8. Chilamkurthy, S., Ghosh, R., Tanamala, S., Biviji, M., Campeau, N. G., Venugopal, V. K., Mahajan, V., Rao, P., & Warier, P. (2018). Deep learning algorithms for detection of critical findings in head CT scans: A retrospective study. *The Lancet*, 392(10162), 2388–2396. [https://doi.org/10.1016/S0140-6736\(18\)31645-3](https://doi.org/10.1016/S0140-6736(18)31645-3)

9. Sahiner, B., Pezeshk, A., Hadjiiski, L. M., Wang, X., Drukker, K., Cha, K. H., Summers, R. M., & Giger, M. L. (2019). Deep learning in medical imaging and radiation therapy. *Medical Physics*, 46(1), e1–e36. <https://doi.org/10.1002/mp.13264>
10. Biswas, M., Kuppili, V., Saba, L., Edla, D. R., Suri, H. S., Cuadrado-Godia, E., Laird, J. R., Marinho, R. T., Sanches, J. M., Nicolaides, A., & Suri, J. S. (2019). State-of-the-art review on deep learning in medical imaging. *Frontiers in Bioscience (Landmark Edition)*, 24(3), 392–426. <https://doi.org/10.2741/4725>
11. Ardila, D., Kiraly, A. P., Bharadwaj, S., Choi, B., Reicher, J. J., Peng, L., Tse, D., Etemadi, M., Ye, W., Corrado, G., Naidich, D. P., & Shetty, S. (2019). End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography. *Nature Medicine*, 25, 954–961. <https://doi.org/10.1038/s41591-019-0447-x>
12. Ma, J., Song, Y., Tian, X., Hua, Y., Zhang, R., & Wu, J. (2020). Survey on deep learning for pulmonary medical imaging. *Frontiers of Medicine*, 14, 450–469. <https://doi.org/10.1007/s11684-019-0726-4>
13. Willemink, M. J., Koszek, W. A., Hardell, C., Wu, J., Fleischmann, D., Harvey, H., Folio, L. R., Summers, R. M., Rubin, D. L., & Lungren, M. P. (2020). Preparing medical imaging data for machine learning. *Radiology*, 295(1), 4–14. <https://doi.org/10.1148/radiol.2020192224>
14. McKinney, S. M., Sieniek, M., Godbole, V., Godwin, J., Antropova, N., Ashrafian, H., Back, T., Chesus, M., Corrado, G. S., Darzi, A., Etemadi, M., Garcia-Vicente, F., Gilbert, F. J., Halling-Brown, M., Hassabis, D., Jansen, S., Karthikesalingam, A., Kelly, C. J., King, D., ... Shetty, S. (2020). International evaluation of an AI system for breast cancer screening. *Nature*, 577, 89–94. <https://doi.org/10.1038/s41586-019-1799-6>
15. Shaikh, F., Dehmeshki, J., Bisdas, S., Roettger-Dupont, D., Kubassova, O., Aziz, M., & Awan, O. (2021). Artificial intelligence-based clinical decision support systems using advanced medical imaging and radiomics. *Current Problems in Diagnostic Radiology*, 50(2), 262–267. <https://doi.org/10.1067/j.cpradiol.2020.05.006>
16. Castiglioni, I., Rundo, L., Codari, M., Di Leo, G., Salvatore, C., Interlenghi, M., Gallivanone, F., Cozzi, A., D'Amico, N. C., & Sardanelli, F. (2021). AI applications to medical images: From machine learning to deep learning. *Physica Medica*, 83, 9–24. <https://doi.org/10.1016/j.ejmp.2021.02.006>
17. Wang, S., & Cao, G. (2021). Review and prospect: Artificial intelligence in advanced medical imaging. *Frontiers in Radiology*, 1, 781868. <https://doi.org/10.3389/fradi.2021.781868>
18. Shad, R., Cunningham, J. P., Ashley, E. A., Langlotz, C. P., Hiesinger, W., et al. (2021). Designing clinically translatable artificial intelligence systems for high-dimensional medical imaging. *Nature Machine Intelligence*, 3, 929–935. <https://doi.org/10.1038/s42256-021-00399-8>
19. Adlung, L., Cohen, Y., Mor, U., & Elinav, E. (2021). Machine learning in clinical decision making. *Med*, 2(6), 642–665. <https://doi.org/10.1016/j.medj.2021.04.006>
20. Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., & Kroeker, K. I. (2020). An overview of clinical decision support systems: Benefits, risks, and strategies for success. *npj Digital Medicine*, 3, Article 17. <https://doi.org/10.1038/s41746-020-0221-y>