# Convolutional Feature Extraction and Multi-Modal Lesion Localisation: AI-Based Systems for Automated Medical Image Analysis and Diagnostic Interpretation

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## 1. Introduction to AI in Medical Image Analysis

Introduction Artificial intelligence (AI) revolves around the use of systems that can perform analysis and make decisions based on prior training. In medicine, including radiology and pathology, tremendous volumes of medical images are encountered every day. AI has the potential to interpret these images with ever-increasing accuracy and process them efficiently. Now, machine learning, a subset of AI, has shown transformative changes when trained on large image datasets for medical image analysis. This provides systems with the ability to learn specific features or patterns and make predictions in a more accurate manner. The advancements of AI in medicine not only add context but also assist clinicians in investigations, diagnosis, and planning of treatment modalities at a much faster pace compared to analog methods. This article discusses the role of machine learning in automating the interpretation of medical images, with an emphasis on radiological and pathological investigations. Additional Key Terms for this Topic Deep Learning: refers to advanced algorithms that use enhanced architectures of computer vision and neural networks with multiple layers to train large-scale databases. Neural Networks: connectionist systems such as perceptrons that imitate the human nervous and decision-making systems. They consist of input, hidden, and output layers and have extensive usage in image processing, voice recognition, and medical imaging. Artificial intelligence (AI) is a branch of science that revolves around the construction of intelligent systems that have the ability to perform analysis and make decisions akin to those performed by humans. In the realm of medicine, AI can deduce decisions at much faster rates and in a much more efficient manner than by using traditional methods. AI in radiology and pathology stands to bring about a revolution in the present era. In radiology, AI can bring effective use of imaging studies for making a diagnosis, planning treatment, and monitoring outcomes, transforming the current radiologist from image interpreters to a more clinically oriented physician. Further, AI can be of great value in decreasing the workload of radiologists in repetitive tasks such as localization and quantification, in addition to boosting the efficiency of radiomics and theranostics. In pathology, AI tools can automate workflows, enhance morphological analysis, decode tumor heterogeneity, and act as an adjunct to increasing the reproduction of clinicopathological studies.

### 1.1. Overview of AI and Machine Learning

Artificial Intelligence (AI) and machine learning are closely related fields. AI is essentially a system that mimics human intelligence. Machine learning is a subset of AI. It is based on the idea that we can build algorithms to enable computers to learn from data. Instead of programming each scenario, machine learning enables systems to learn through experience and the input of data. The purpose of machine learning is to learn to make accurate predictions or useful decisions without the need to explicitly write logical statements to receive a desired result. Supervised learning, unsupervised learning, and reinforcement learning are commonly used techniques in healthcare settings. In image analysis, machine learning algorithms are trained with large datasets of various images. The size and richness of the data that is used to train the algorithm have an impact on its accuracy. The more data available, the more precise the analysis will be. It's not just about the volume of data; there is acknowledgment that diversity has to be accounted for. As such, huge interest in deep learning techniques is being witnessed as results point to a decreased need to anonymize, making the data richer and more diverse. Newer deep learning networks are demonstrating capabilities for classification, segmentation, as well as localizing lesions or regions of interest. These advancements have opened up a wide range of possibilities for diagnosis and treatment of diseases. AI technologies constantly learn to recalibrate what they have been trained on and continue to evolve. This technical revolution has seen exponential growth in technology and interest across multiple sectors and the growth of commercial organizations professing to be experts or leaders in AI across the globe. Aspects of AI being used in medical imaging, such as data annotation and models, will be the focus of this text.

### 1.2. Applications of AI in Radiology and Pathology

1.2. Applications in Radiology and Pathology AI in Medicine has published various research efforts wherein AI system models were formulated and utilized as versatile tools that complement existing radiology and pathology practices. The models are tasked with performing specific functions such as multi-modality imaging diagnostics, as in the case of data from positron emission tomography–computed tomography and T2 fluid–attenuated inversion recovery magnetic resonance imaging, whole slide imaging for the purpose of differentiating between Grades 2 and 3 versus Grade 1 in meningiomas, and early detection of brain metastases in comparison to CT in six tumor types.

AI in Medicine further discusses the various functionalities of AI in radiology, such as whole-body MRI processing, pancreatic tumor detection, and distinguishing between asymptomatic and symptomatic vertebral hemangioma. In multidisciplinary collaboration, it is proposed the use of generative adversarial networks in magnetic resonance imaging post-processing. This seeks to improve the resolution of low-quality images sub-sampled at 15% on AI-ready workstations. The reduced time for image evaluation can serve as a significant time-saver during the aorta evaluation process. AI in Medicine discusses the aid of AI in pathology with a review of systems designed for the detection of retinopathy, skin cancer, tuberculosis in histopathological images, lung histology image triaging, colorectal polyp classification, Barrett's esophagus detection, breast cancer detection, prostate cancer detection, and grading. Additionally, the review expanded on gastrointestinal disease triaging. However, there is yet to be a comprehensive review combining systemic anomalies. AI in pathology is thus capable of detecting a diversity of anomalies and diseases. The use of AI systems offers the potential to complement current radiology and pathology practices. These systems are proposed as tools that radiologists and pathologists may include within their clinical decision-making process. It is carefully highlighted that many current AI systems are still in development and require further trialing prior to being widely integrated across the healthcare framework.

## 2. Challenges and Opportunities in AI-Based Systems

AI-based systems can bring disruptions by automating and transforming the field of medical image analysis. A machine learning model is effective in performing the tasks if it is trained with a representative dataset that covers all possible diseases and is as unbiased as possible. Despite the ongoing success stories and manifold possibilities that have reportedly been successful in the research literature, many challenges need to be resolved to integrate AI-based systems into clinical operations. For medical image analysis in particular, one of the greatest challenges lies in representing human body parts in 2D/3D, capturing the whole spectrum of normal and abnormal conditions, and being robust enough to compensate for the variance in the dataset. In the field of radiology, once the AI model is trained and approved, it will be part of everyday clinical operations, and thus the AI system will need to be upgraded and adapted to different demographic client groups and clinical applications.

Despite the aforementioned challenges, for both pathological and radiological applications, AI is expected to lead to enhancements in operational efficiency. AI systems hold the potential to raise clinical diagnostic performance in terms of diagnostic accuracy by extracting subtle information that may be missed by human observers. Health data scientists need to work and communicate effectively with healthcare practitioners. Data science research teams need to collaborate with radiological and pathological teams and ask for domain-specific inputs to overcome data bias and related side effects. Similarly, a broad sense of integration of data from genomics and other

**2.1. Data Quality and Quantity**

One of the most critical components of successfully developing AI systems for medical image analysis is obtaining high-quality data. The quality and quantity of available data have a direct impact on the performance and generalization of models trained using this data. The use of annotated data, especially for supervised learning, is highly important given the goal of training accurate models to automatically perform the tasks of interest in radiology or pathology. However, there are several challenges related to the datasets used for AI-based systems. The scarcity of available data when trying to train data-hungry deep learning models and the variation in appearances between images acquired using different medical imaging modalities have motivated the development of different techniques to generate synthetic data that mimics intra-modality variability. Addressing the need for higher quality annotated data for developing AI-based systems in medical image analysis has attracted several research and commercial efforts. A few practical considerations that are particularly relevant to radiology and pathology medical imaging datasets include the need to protect sensitive patient information, the use of large and publicly available medical image repositories in research, the negative impact of drawing information from biased datasets when training AI models, and the variation in characteristics of radiological and pathological images. Therefore, navigating data challenges is a critical consideration for the successful implementation of machine learning models in medical image analysis. Many applications are designed to be versatile and capable of learning from a range of data inputs, including different imaging techniques, pathologies, and non-pathological variations in appearances.

### 2.2. Interpretability and Explainability

Interpretability is commonly recognized as essential for the translation and adoption of AI models and algorithms in clinical practice. It refers to the capacity to understand and explain the results and decisions made by an AI algorithm. The proposed AI model should be transparent and understandable to non-specialists in AI and machine learning. In fact, there is a general lack of trust and acceptance towards so-called black box algorithms that provide knowledge concerning how decisions were made. Due to their non-transparent structure, conclusions reached are not verifiable or explainable. This veil of secrecy, concealed by AI algorithms, constitutes the greatest hurdle in the development and acceptance of AI tools by healthcare. It is not only a technological challenge to create a transparent AI but also an essential ethical requirement to explain decisions reached by an AI system. Imperatively, healthcare professionals expect an AI method to be as understandable and interpretable as transparent by the system creator. Healthcare professionals require correct decisions made by AI and are willing to adopt these systems as part of routine clinical practice; this may be more readily achievable through transparency concerning proposed models.

An ethical imperative to explain AI algorithm decisions is required with applications in the healthcare field, where it could impact patient care. Thus, it is possible that the gradual adoption of transparency-compliant AI techniques by companies and organizations initially made them more easily trustworthy, thereby incentivizing their adoption. Ideally, such AI tools could complement or even replace some particular standard-of-care testing. Overall, the application of explainable AI techniques should be considered in AI systems and should go hand in hand with the superior performance of such systems.

In conclusion, the application of AI systems in healthcare clearly requires not only demonstrable clinical utility and safety but also interpretability. The requirement for increased interpretability might also come from regulatory bodies calling for explanations of complex AI decisions in order to ensure patient safety. Decisions made by AI algorithms will not be taken directly by the detainee, but if decisions can be reached via a transparent route, they do not require further explanation. Therefore, transparency and interpretability of AI are important aspects that can facilitate societal and governmental adoption of AI applications with major consequences.

**3. Technological Foundations of AI in Medical Image Analysis**

In recent years, advanced deep learning architectures such as convolutional neural networks (CNNs) have become increasingly popular to handle medical images. CNNs have a unique way of constructing artificial neural networks, targeting lower computational complexity as opposed to traditional multi-layer perceptron networks. They also rely on a significantly reduced number of randomly initialized weights and thresholds, which still results in almost state-of-the-art and highly accurate feature representations for typically high-dimensional image data. CNNs do not require pre-engineering of suitable features, as they learn suitable representation levels automatically from the available data. Due to their pretrained representation strides, CNNs can handle high-dimensional data more effectively, highlighting a certain hierarchy of feature representations based on intensity and textural information, as well as higher-level abstracted characteristics and structures. These features are continuously built one based on another and, in the end, result in highly sophisticated and abstracted data representations. The integration of various machine learning techniques with medical images has always been a central research field with profound intentions to improve clinical processes and diagnosis. Researchers have stated that leveraging machine learning models is deemed highly important to boost image analysis capabilities to the next levels as well as to substantially reduce area-sensitive system downtimes. Of course, there are also substantial challenges that need to be addressed, such as the still somehow low model interpretability, explainability, actionability, and especially the validation of the systems in broad clinical practice to gauge their impact on daily work as well as on clinical outcomes. Many works have been released recently that address some of these opportunities and challenges, indicating a rising trend towards the design of hybrid systems that are able to cover a plethora of clinical procedures with trustworthy and reasonable performance.

### 3.1. Deep Learning Architectures

Deep learning is a subset of machine learning based on artificial neural networks that have the ability to automatically learn data representations from large amounts of data. In deep learning, there is a great interest in the use of convolutional neural networks (CNNs) - one of the most common architectures for deep learning, which has significantly improved image recognition and computer vision tasks in recent years. One of the first and most successful deep CNNs was AlexNet, which helped to classify the ImageNet dataset into 1,000 different categories. This architecture has been widely used, showing great potential in many other applications. CNNs consist of a set of layers that capture three key operations. The layers present in CNN architectures used for image recognition mainly include convolutional layers, pooling layers, and fully connected layers. - Convolutional layers: Each layer involves a convolution operation that processes the input data with a learned convolutional matrix. In this stage, the local features are captured from input images. - Pooling layers: This layer uses different operations such as max pooling or average pooling to reduce the coverage of the output feature map from the previous layer. This layer guarantees that the model is close to invariant to the translations and rotation of the input image and has some robustness to orientation or distortions of the input image. - Fully connected layers: This layer is involved at the end of the architecture, implementing the function of combining the local features learned during the early layers of the architectures, offering a high-level representation of the input image. It is used to reduce the spatial dimension of the input image into a one-dimensional vector in order to forecast the desired output class. Studies indicate important architectures specially developed for the medical domain, such as U-Net and ResNet; these two architectures offer high-level representation. However, following this strategy, along with the significantly improved accuracy of deep learning models for medical images, there are many challenges that must be addressed. Challenges in Training The foremost challenge in deep learning is overfitting. Training a deep CNN from scratch on limited medical imaging data can cause overfitting due to the large number of initial unknown parameters, resulting in poor performance in evaluation testing. While overfitting can normally be resolved using some type of regularization, deep networks need a specific type of regularization because of the large number of parameters.

**3.2. Computer Vision Techniques**

The analysis of medical images by computer vision techniques has been extensively studied and is an active area of research. Many computer vision techniques are used for medical image analysis to augment AI-based systems. Image segmentation is commonly used for this purpose. Segmentation is the process of partitioning the image into different regions or objects such as normal tissues and tumors in medical images. The complete image segmentation constitutes different types of processes like preprocessing, feature extraction, and pattern recognition. Thus, a good medical image segmentation technique should include these basic processes to achieve a good level of accuracy.

Although the methods proposed for medical image analysis are based on the principles of traditional computer vision techniques, artificial intelligence (AI), particularly machine learning, has been used to improve segmentation accuracy in recent times. Machine learning is an area of AI research that allows the system to learn from experience. This is achieved by supplying an algorithm with large amounts of data from which the algorithm extracts patterns. Once significant patterns have been found, the system is trained to recognize and use these patterns for decision-making. Methods such as edge detection are common steps in almost all the preprocessing steps used in medical images. They are generally used to highlight the regions inside the image. Morphological operations such as dilation and erosion are widely used for most of the medical image preprocessing steps. Histogram equalization techniques have been exploited to increase image contrast, which ultimately improves the clarity of the images. The power of AI for medical image analysis enables overcoming limitations related to traditional computer vision techniques. Machine learning alone or combined with computer vision techniques can improve the performance of medical image analysis to a great extent. This integration has led to encouraging results in a variety of clinical tasks ranging from tumor segmentation to organ delineation.

Medical data vary in different aspects, creating challenges for medical image analyses for use in CAD-based AI models. One of the barriers is the unstandardized acquisition protocols, which result in varying quality of imaging. Secondly, the imaging process is itself a source of patient-associated artifacts. Such drawbacks can be suitably addressed with AI, where the system can be trained with a sufficient variety of inputs, ensuring a robust decision in the presence of different imaging qualities. Hence, it is recommended for optimized CAD in the field of imaging to leverage both computer vision and machine learning to improve the outcomes of the analysis of medical images in reducing heterogeneity in different studies.

**4. Case Studies and Success Stories**

It is one thing to argue that machine learning paradigms can dramatically enhance the search and analysis of medical images, but quite another to demonstrate. For this purpose, we present here some case studies and several success stories that include state-of-the-art benchmarking of AI-based systems. The case studies described are not only under regular use in daily clinical diagnostics with thousands of scans being analyzed per month, but they have also undergone rigorous retrospective testing with exact retrieval of results. Here, we present the description and performance of these systems. The tested brain volume quantification and brain structure segmentation algorithms have grown out of deep learning frameworks. Both algorithms used a transfer learning approach, employing a pre-trained convolutional neural network that has been trained on non-medical natural or object images. Preprocessing was performed in both cases. Another algorithm used deep learning for the identification of hypertension in retinal fundus images.

The area of decision-making diagnostics is intriguingly different from that of volume quantification and structure segmentation, although successfully approached in a similar manner. Here, a rare morphological marker indicating essential genetic information makes all the difference. Other challenges can be even more complex than black box prediction. It is the poorly understood functional implication of the diagnostic area in the human visual cortex for depression that commands attention. For yet other tasks, merely the identification of patterns in an extensive data matrix is clinically relevant since only such big data reanalyses will uncover otherwise unknown treatment effects. The algorithms presented demonstrate not only the capability of machine learning approaches in the field of medical decision support and diagnostics. The deep learning-based image analysis solutions described demonstrate that such systems are broad in their potential applications. They show the outstanding potential of machine learning systems that have been developed to learn from millions of diagnostic cases.

This promises great efficiency that is preferable over traditional systems in human-based image analysis.

### 4.1. AI Applications in Radiology

Radiology is a medical specialty that employs the use of imaging to diagnose and treat diseases seen within the body. Two major types of radiology include diagnostic radiology and interventional radiology. While diagnostic radiology is the diagnosis of disease using images such as X-rays, CT scans, MRI scans, or ultrasounds, interventional radiology is a sub-specialty of radiology involving minimally invasive procedures guided by imaging. Radiology is a profession in which radiologists use medical imaging to diagnose and treat diseases. It has gone beyond just the duties of radiologists and is now a field in which artificial intelligence may be applied. With advances in machine learning methods, computers have become increasingly capable of performing practical tasks that usually require human intelligence. Moreover, radiology is a specialty that relies heavily on visualization, thus making it feasible for AI applications. Major applications in radiology can be classified into computer-aided detection and quantitative image analysis, with both focusing on the accurate interpretation of medical images.

Automating medical image analysis for radiology tasks: Automating medical image analysis using artificial intelligence has become a trend in the past few years, mainly for diagnosing distinct types of diseases, detecting specific regions that present the disease, or segmenting the region by quantifying the target volumes. In quantitative radiological image evaluations, tasks such as lesion detection, localization, and classification have been performed. In diagnosing diseases, AI uses machine learning on vast amounts of patient data to recreate human-like decision-making beyond the scope of standard medical imaging. Backed by deep learning algorithms, AI-based systems designed to read specific categories of radiological images automatically provide analysis or highlight the required portions, helping radiologists respond to emergencies better, analyze images faster, and interpret the results more effectively. The most common radiological images that use AI-based systems are X-rays, MRIs, CT scans, and mammography. These techniques can be applied in quantitative and sentimental radiological analysis accurately. Since quantitative and sentimental analysis are essential components of a comprehensive medical image evaluation, the use of AI is set to enhance the field of radiology.

**4.2. AI Applications in Pathology**

Pathologists also benefit from artificial intelligence developments through diagnosis support tools. When deep-learning methods are used, they should input on models and AI processing pipelines that integrate human-like intelligence in a way that doctors can make more intuition-driven decisions. The rapid development of digital pathology signals that digital diagnosis has great potential. Tools such as histopathology image analysis can better analyze the complexity of information and identify patterns that are often very difficult to decipher by human beings.

With the use of machine learning, pathologists are likely to see a new level of authenticity in their revolutionary world through higher probe efficiency. Thanks to the use of AI, not only can pathologists better deal with their overload problems and deliver medical services, but they will also offer the best diagnosis and treatment to people. AI enables robots to perform physical and repetitive tasks more reasonably and efficiently. For similar reasons, AI is used in digital pathology to perform automated scanning and to present the digitalization. Scenes from an individual slide can be done in less than a minute, which is typically less than a quarter of the time a human stakeholder would require to do the same task.

**5. Future Directions and Ethical Considerations**

Future directions

The future directions in the field encompass AI and radiology, an example being personalized medicine, the role of AI in radiogenomics, omics imaging, assessment of lesions, including both neoplastic and inflammatory, and opportunities for AI in predictive analytics. Furthermore, AI is expected to revolutionize the healthcare paradigm from "patient care" to "patient engagement," which would consider the active participation of patients and encourage better control of their own well-being.

Regarding ethical AI, the most important issue is the protection of patient privacy and their well-guarded health data, including the security of data in AI, as well as issues related to consent for processing and the intermodal use of patient data. There is an urgent need to develop a framework for policy, research, and regulation, and to develop new models of collaboration between technology developers and stakeholders, including radiologists, pathologists, and representatives of regulatory authorities. Work is also needed to ensure diversity, non-discrimination, transparency in decision-making, and independence in scope correction. The issue of "organizational bias" could be as significant as it becomes a challenge for all algorithms in the sense of "Garbage In, Garbage Out." Above all, it is important that everyone starts training and detecting harmful biases inherent in AI applications to establish a mechanism for continuous governance. It is essential to consider the ethical aspects underlying each AI development process, thus defining how to steer the opportunities stakeholders should be encouraged to explore and to identify and address the risks to the protection of healthcare information. We expect AI to play a role in the dynamics by helping a system at least to run smoother. It can undo some of the mistakes and make up for some of the time lost for the patients, but all of this will require a balanced approach between enthusiasm and prudence for us to benefit from AI.

### 5.1. Emerging Trends in AI for Medical Image Analysis

In this section, we will shed light on some of the emerging trends in AI for Medical Image Analysis:

Real applications: AI is increasingly being used to develop prototypes with analyses in a real-time setting to translate these research outcomes. AI can be completely integrated into various imaging processing tools or modules used in telemedicine applications where physicians or technology is not available.

Personalized approach: Personalized medicine is essential in healthcare. It can be used to provide patient reports based on X-rays and pathology imaging.

Access to healthcare: AI enables accurate automated reporting, which helps to connect expert reports related to radiology and pathology directly from a remote location as necessary. Furthermore, in routine cases, AI can assist in making automatic diagnoses by radiologists or pathologists for neurology, radiology, nuclear medicine, or surgery. AI permits diagnostic imaging to be reported more widely in secondary or tertiary level centers or high-quality outpatient and emergency cases where no credits exist.

Interdisciplinary collaborations: The use of interdisciplinary computer-aided design technologies is very important. The categorization of images and pre-screening of pathological histopathology images are also significant problems in classification systems. AI plays an important role in engaging healthcare and industry to develop specific products. The majority of the methods, tools, and applications distinguish the patterns of X-rays, magnetic resonance imaging, and histopathology images as normal or pathological from the radiology perspective. The importance of medical imaging and emerging trends from the research development point of view is to select pure CAD-XRBs.

Hybrid AI models: Integrated (both handcrafted feature-based and end-to-end learning-based/machine learning) CAD models are also recently growing to yield better outcomes and eliminate overfitting and underfitting programs. The theme of this conference, Healthcare Image Analysis, is the selection of hybrid healthcare operators with MRI, neuro-radiological images, histopathology records, and other sources. A variety of AI/ML operators would also be employed, including CT, PET, ultrasound, single-photon emission CT, angiography, and other radiological imaging. In the long term, we expect many interdisciplinary projects, including healthcare and AI, and we also offer the opportunity to explore pure AI.

Data democratization and the rise of citizen scientists: With a vast amount of information about radiological imaging and histopathology, we expect to see a large number of papers in these sections. These will also act as citizen scientists, creating medical images for the public that could potentially be used in cancer research.

The increasing role of AI in healthcare research: The application of bioimaging techniques for genomics research is potentially becoming a new way forward, not only in healthcare research but also in other diseases. This is combined with efforts in image and genomics data integration and deep covariance modeling techniques to improve signature discovery from diverse image sources for the return of absolutely reliable results.

### 5.2. Ethical and Regulatory Frameworks

The increasing importance of AI applications in patient imaging prompts the necessity to set up ethical and regulatory frameworks. Principally, bi-directional trust is essential in achieving the users and applications synergy among patients and healthcare providers, as well as encouraged innovation and socio-economic impact sustainability.

The added value given by trust in AI models incorporates, in particular, the improvement of interpretability and the algorithms' accuracy resulting in better image interpretation. As trust is a human-based feeling, the inclusion of AI applications in the healthcare process encourages maintaining ethical awareness, since machine learning-based image analysis raises a series of issues. They also create a natural resistance to a radical change in methods of interpreting disease perception. Relevant for ethical dilemmas, a series of key domains have been of interest including the impact of automated decisions, the impact of machine learning on radiologists and pathologists' psychology, the impact of diagnostic change on healthcare systems and society, and the implications of algorithmic bias and data misuse.

As mentioned, the guidelines stated for adopting AI systems into the clinical routine are complex yet essential. Several deliberations were discussed assessing the current international algorithm guidelines and attempting to elaborate best practices for optical radiation exposure. While the development and introduction of AI-supported image analysis clearly raise complex social, ethical, economic, and clinical concerns, the experience of several countries indicates a number of technologically non-specific criteria to be considered, as summarized below. The development of a regulatory perspective on these issues requires an ongoing dialogue considering stakeholder perspectives as well as emerging technological development. Regulatory concerns and information about best practices for the integration of AI systems into the healthcare system can be expected to evolve proportionately with our understanding of AI and the specificities of AI applications in clinical imaging. Additionally, it is important to allow the necessary flexibility for continuous improvement in AI technology, through, for example, avoiding over-specifying concrete performance thresholds and benchmarking techniques in early regulatory frameworks. It can additionally be expected that AI-specific regulatory concerns will have to address the question of adaptable healthcare system regulations to AI deployments and consider requirements for post-market audit and registry to ensure ongoing safety and performance in an area of technology likely to see fast-paced innovation and early adoption.

## 6. Conclusion

This essay has provided deep coverage on AI technologies for medical image analysis, particularly in pathology and radiology. Results suggest multiple advantages of using

AI-based automated image analysis systems, including their potential for enhanced accuracy, efficiency, reliability, speed, and cost-effectiveness. The potential of AI is particularly useful in automating repetitive and time-consuming tasks for medical staff, including annotating, feature extraction, and segmentation. Such systems may have a key role in a comprehensive quality improvement program. Their design will allow them to detect and quantify errors during any phase of image acquisition, decreasing potential sources of variability. Given these potential advantages, much remains to be done to establish best practices in image analysis with AI. There is an urgent need to improve data quality and establish regulatory and ethical standards for development, evaluation, and deployment. We conclude that the AI may be a fruitful avenue for resolving these problems, especially given the trends towards larger and more complex data. Publicly available annotated databases are available for clinical and nonclinical practice, and they include patient safety-related objects such as tumors, blood vessels, and bones as well as blood cells and dermatological diseases. However, the large number of available databases indicates that several open learning challenges remain unsolved, demonstrating the potential to address new applications and transfer learning.

In recent publications, AI algorithms have performed well in clinical practice, with various applications in disease detection, localization, and grading. More and more research is focusing on explaining learning advancements and producing models that better satisfy physicians with respect to interpretable and explainable results. A fundamental question is the trade-off between black box systems for performance and judgeability, a trade-off that depends on clinical requirements, the technology stack employed, and the system users. While considerable progress in interpretability has been achieved, there is still much unclarity, and novel classification techniques need to be interpreted and validated. Other issues discussed in this paper include data security and privacy, fake X-rays in radiology and cybersecurity attacks, and workload distribution. AI significantly improves the quality and performance of health care, for instance, by providing assistive diagnostic imaging solutions. We assume that greater penetration of AI systems in clinical settings and based on the perspective of regulatory and legal issues, it is essential to improve confidence by facing and solving open challenges. We invite academic and industrial researchers as well as clinicians, ethicists and legal practitioners to contribute to computational problems across various images and data acquired.