SJIF Impact Factor: 6.711

WORLD JOURNAL OF ADVANCE HEALTHCARE RESEARCH

ISSN: 2457-0400
Volume: 9
Issue: 8
Page N. 315-337
Year: 2025

Original Article www.wjahr.com

ARTIFICIAL INTELLIGENCE IN HEALTHCARE: BRIDGING INNOVATION AND CLINICAL PRACTICE

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Article Received date: 20 June 2025 **Article Revised date**: 10 July 2025 **Article Accepted date:** 31 July 2025

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ABSTRACT

Artificial Intelligence (AI) is turning the healthcare sector upside down, due to its ability to improve the analytical accuracy, treatment planning, and automate administrative work. The review therefore in detail covers the various functions of AI in a cross-sectional manner across various therapeutic topics, which include but are not limited to radiology, oncology, cardiology, gastroenterology, ophthalmology, and surgery. The research points to the paradigm shift that appliance learning (ML) and deep learning (DL) can have in the reading of compound medical statistics, speeding drug discovery and making long-term conservation personal. It also focuses on key initiatives including through confidentiality of data, algorithmic bias, principled governance, as well as clinical integration. As the number of submissions in image acknowledgement, predictive analytics, and virtual delivery of healthcare has been on the rise currently, AI has a tremendous potential to ensure that the existing gaps in healthcare systems all around the globe are attended to. Nevertheless, in order to be successfully implemented, it requires potent infrastructure, multi-disciplinary partnership, and constant verification so that the outcomes of healthcare are ethical, equitable, and reliable.

KEYWORDS: AI, Deep Learning, Machine Learning Oncology, NLP.

INTRODUCTION

Medication is being transformed in such a way that AI is intended to bring immense changes with the potential of improving clinician and patient outcomes. After two years of effort, weekly effort, we make important reports of making breakthroughs in clinical AI. We make comments on future studies and developments in the field of medical image analysis that have created a linkage between research and implementation. Some of the recent promising directions in medical AI that we comment on are non-image data, new conciliations of the issue formulation, and the collaboration between humans and AIs. Lastly, we discuss serious technical and ethical issues; such as the lack of data to prejudice based on race. With these impediments out of the way, the potential of AI can be achieved, carrying healthcare into more accurate, effective, and accessible directions to patients worldwide.[1] The introduction of AI will change medication in its very essence and potentially increase the outcomes of both clinicians and patients. We make important conclusions after a two-year-long effort to achieve path and reveal significant breakthroughs in medical AI. We present the future scientific studies and medical image analysis that have provided a difference in the imminent medical analysis and practice. We mention the future trends in medical AI based on non-image data sources, novel formulation of issues, and collaboration between humans and AI as some of the zones where future research on AI in medicine is interesting. Lastly, we touch on some critical technical and questionable issues such as the lack of data and even race discrimination. With these concerns being addressed, AI can be utilised to realise its potential better, making the healthcare system more accurate, precise, and accessible to patients around the world.[2] AI will be used to transform medication fundamentally, potentially increasing clinical outcomes and patient ones. After two years of weekly effort on path and after hundreds of posts on medical AI, we draw important conclusions. We also talk of prospective research and breakthroughs that have made a difference in medical image analysis that hyphens research and application. We also present other interesting future medical AI research directions that include non-image sources of data, more interesting formulation of issues, and human and AI collaboration. Last but not least, we mention valuable technical and ethical issues such as the lack of data and racial bias. Overcoming them, the potential of AI can be achieved, so healthcare could be highly accurate and efficient and available to more patients worldwide.[3] AI system is intended to change the foundation of medication, which may enhance clinician and patient outcomes. After two years of weekly effort in the direction of path and publication of important advances in medical AI, we emphasize important findings. We report on the future of some upcoming research and developments in medical image analysis that have filled this research/application gap. We also address the mention of some interesting future research topics of medical AI like non-image data, out-of-box issue formulation, and human-machine cooperation. Last but not least, we deal with significant technical and moral issues such as data lack or racial bias. With the presence of such issues being resolved, the capabilities of AI can be realised and healthcare can become more specific, optimised, and closer to patients wherever they are in the world.[4] The intelligence is meant to radically transform medication, which may increase the efficacy of clinicians and patients. Two years into our weekly effort to get at path, we point to some crucial findings and to milestones in medical AI. We argue about future research and innovations in medical image analysis that have led to the merging of research and practice. We also mention some promising directions in which medical AI research can be performed in the field of non-image data sources, formulations of new issues, and collaboration between people and AI. Lastly, we handle critical technical and ethical issues that concern the lack of data to racial bias. The potential of AI can be achieved as these concerns are settled, and healthcare can thus be more specific, effective, and available to citizens around the world.[5]

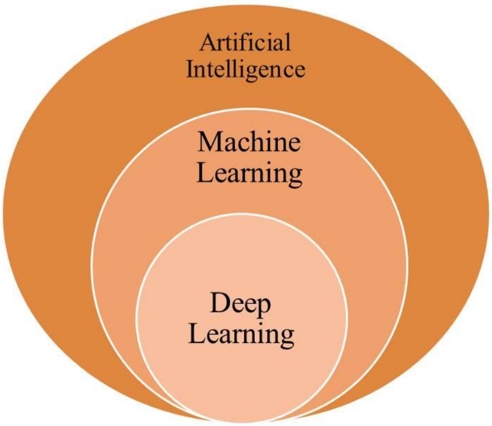


Figure 1L: Diagrame of AI, ML, DL Classification Of AI, ML, DL.

WHAT IS ARTIFICIAL INTELLIGENCE

In a nutshell, AI studies and designs the engineering procedures of developing sensible machines that can mimeric workings of the human brain through algorithms or a block of rules such as learning and problem-solving processes. An AI system is methodical, smart, and flexible since it is either ready to anticipate a predicament or deal with it on the fly. By analysing the entire medical history of a patient, the AI systems could incur it into one number that suggests possible diagnosis showing the power of the technology in learning and deriving patterns and connections to massive datasets that are multidimensional and multimodal. Additionally, AI systems are independent and adaptive and modify according to the new data and learn. Rather than consisting of one, omnipresent technology, artificial intelligence (AI) is a conglomeration of a few subfields, such as machine learning and deep learning, which individually or in hybrid combinations make applications smarter. The research of algorithms which allow computer programs to improve automatically over time is called machine learning (ML). ML can be in turn split into the classes of supervised, unsupervised, and reinforcement (RL) ML, and research in many of the sub-fields (semi-supervised and self-supervised ML, and multi-instance ML) is ongoing.[2] In plain terms, AI refers to an engineering and scientific study of producing intelligent machines that employ algorithms or rules sets to simulate human cognitive processes such as understanding and resolving. The reason behind this is that AI systems also operate in a goal-oriented, intelligent and flexible manner since anything that needs to be predicted can be predicted, or when problems occur they can be tackled. Artificial intelligence could turn the full history of a patient into one figure that suggests a probable diagnosis, and the technology would prove to be powerful in learning and determining the pattern and connection within an enormous and multidimensional and multimodal data. Moreover, AI systems are independent and adaptive, they learn and evolve as they respond to new information. Rather than being an all-purvasive and one technological sphere, artificial intelligence (AI) is constituted by a series of subfields, such as machine learning and deep learning, among others, which independently or combined make applications more intelligent. Machine learning (ML) is the study of algorithms which allow the computer program to improve itself automatically over time. ML can be divided into classes of its own: 'supervised', 'unsupervised' and 'reinforcement learning' (RL) and research continues in other sub-fields such as 'semi-supervised', 'self-supervised' and 'multi-instance ML.[6]

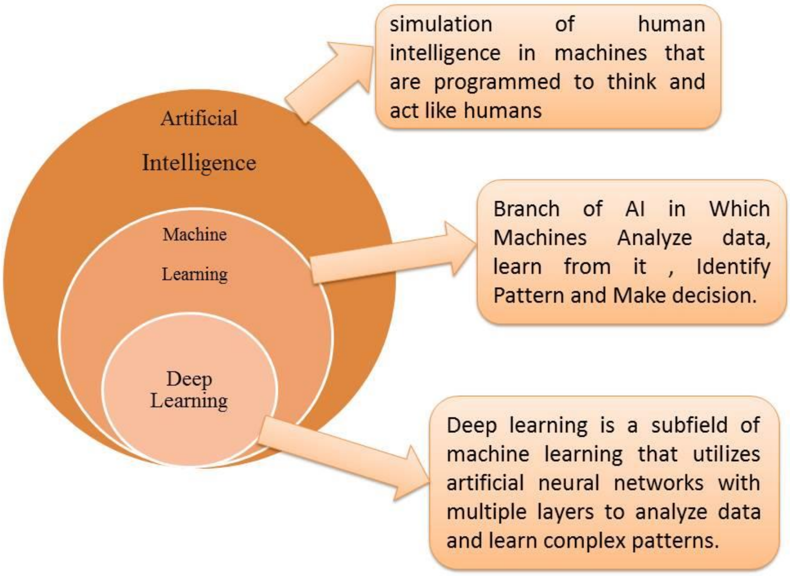


Figure 2: Main constructs of artificial intelligence.

WHAT IS AI IN HEALTHCARE

Artificial intelligence in healthcare is the implementation of technologies that are based on artificial intelligence, e.g., machine learning and natural language processing, to enhance healthcare provision, diagnosing, treatment planning, monitoring patients, and the administrative process. It covers the use of algorithms on complex medical data to make predictions or recommendations that make clinical decisions and lead to patient outcomes. AI in healthcare is aimed at making processes automated, more patient-centered, the medical error less common, and eventually make the work of medical personnel more efficient and effective. Artificial intelligence (AI) tries to imitate the human thought process. It is changing how things are done especially in the field of healthcare because of increasing accessibility of health data. More speedy and accurate new procedures of analyzing this data are also emerging.[7] Artificial intelligence in healthcare AI in healthcare is the practice of applying artificial intelligence technologies, e.g., machine learning and natural language processing, to enhance the delivery, diagnostics and treatment planning, patient monitoring, and administrative aspects of healthcare. It is a process in which a complex medical data is analyzed using algorithms where predictions or recommendations, as a result of clinical decision-making, are made and used to improve patient outcomes. The aim of AI in healthcare would be to automate procedures, offer customized care to patients, minimise medical errors and ultimately enhance the effectiveness and efficiency of healthcare services. Artificial intelligence (AI) is meant to imitate human thought. Within the healthcare industry, it is already revolutionizing the work by the increased accessibility of healthcare information. Also, novel ways to analyze the said data are getting quicker and more precise every day.[8] AI healthcare can be defined as the application of the artificial intelligence technologies (including machine learning and natural language processing) to enhance the provision of healthcare, diagnosis, treatment planning, patient monitoring, and administrative process. It entails the use of algorithms to evaluate intricate medical information and make predictions or suggestions that can benefit clinical decisions making and patient outcomes. The objectives of AI in healthcare are to achieve automation of activities, personalization of medical care to patients, minimization of medical errors, and eventual improvement of efficiency and effectiveness of medical services delivered. Artificial intelligence (AI) is supposed to simulate the human mind. It is changing the face of things in the field of health care where healthcare information is becoming more and more accessible. Moreover, the new ways of analyzing this information become quicker and more precise.[9] The other essential use of AI in healthcare is remote monitoring. Remote monitoring systems with the AI feature enable the constant monitoring of the vital signs of patients to detect any possible issues and address them in time. This allows an earlier response and enhances patient outcomes and limits the need to visit healthcare facilities physically. Another manner through which AI is improving the delivery of healthcare is virtual consul-tation. The provision of healthcare remotely helps to offer care and treatment without the need of transporting the patients as this is very convenient to patients in isolated or inaccessible places, or those with limited mobility. The technological innovation of Artificial Intelligence (AI) into medical radiology can boost the quality of patient experiences and a significant increase in accuracy of the diagnoses. AI can improve radiology in some ways so that most medical conditions can be diagnosed and treated using this vital area of study. This is one of the main applications of AI in radiology: to analyze medical images and extract useful information therein, including, but not limited to X-rays and CT scans. The picture of various conditions can be studied with the help of AI algorithms, and anomalies may be discovered and contribute to the condition diagnosis. This will enhance speed and precision of the diagnoses and eventually result to improved care of the patients. Also, AI can automatically identify any lesions on medical images, which also decreases the possibility of an incorrect diagnosis and enhances the outcomes even more. AI is also able to process both the medical images and data on patients to make projections of the development of the disease, in the case of cancer, contributing to the customization of the treatment plan.[10] Artificial intelligence (AI) is the term describing the growth of computer systems that can be used to complete human-dependent jobs that normally need intellectual capacity. In healthcare, AI is found in different forms as they include machine learning algorithms, natural language processing, and robotics.[11] Such technological features allow machines to process complicated medical information, detect traces, and form a professional conclusion. Consequently, AI successfully brings improvements to the skills of medical workers.[8] AI in health care is a radical change that affects the interaction with patients, the planning of treatment, administrative activities, and diagnostics. Its main objectives are to enhance the outcomes of patients, improve the process of providing healthcare, and improve the quality of care. An AI is not a one-sided solution; it is an array of instruments providing numerous applications applicable to diverse phenomena of the healthcare system.[12]

DEEP LEARNING

Deep learning (DL) is a subfield of machine learning, and it concerns neural networks that have more than two layering which make them able to generate high-level abstractions out of raw data.[13] Its growth is directly related to more computing performance, wide access to large data sets, and new algorithms.[14] In comparison to classical machine learning where the features are engineered, deep learning automates the process of feature extraction providing an improved complex task performance.[15] This aspect of artificial intelligence Deep learning is a sub-field of machine learning and has become a fundamental part of contemporary artificial intelligence (AI) by allowing a machine to automatically find patterns in data with minimal or no human intervention.[13] The artificial neural network is the basic component of deep learning and it is a group of neurons that communicate through the layers that resemble the neurons in the human brain.[13]

Applications of Deep Learning

- **Deep learning had its multiple applications in nearly all fields**
- **Healthcare**: Deep neural networks (DNNs) have proved to be valuable elements in the field of healthcare especially in the fields of medical image analysis, early disease diagnosis, drug development, and design of customized treatment plans.[16]
- **Adopting, Autonomous Systems** • Self-driving cars solve with CNNs, plus negative making use of reinforcement learning.[17]
- **Natural Language Processing**: The transformational framework of BART and BERT have changed the language translation, sentiment analysis, and question answering.[18]

MACHINE LEARNING

Machine Learning is a fundamental part of Artificial Intelligence that gives systems the capacity to learn based on the information, identify patterns and naturally take decisions with less human intervention. Unlike in rule-based programming, ML systems learn knowledge based on exemplary cases rather than having to be limited to prescriptive guidelines to them; hence, the ability to constantly adapt to unseen data. The classical classification of ML algorithms includes three major groups, namely supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, algorithms are educated on labeled data so as to predict outcomes in terms of pre-expressed features. Unsupervised learning refers to the inferring of latent structures of unlabeled data and is therefore especially applicable in applications (such as clustering and dimensionality reduction) in which labelled data is not available.[19] Reinforcement learning models embrace an experience-aided, step-by-step procedure to unraveling the best policy through the intervention of their surroundings by a correlation of awards.[20] Reinforcement learning models learn to exhibit ideal behaviours in an incremental manner and they are guided by rewards.[13] Conventional Neural Networks (CNNs) present the current image recognition paradigm, and recurrent Neural Networks (RNNs) are the most popular in natural language processing. The best way to perfect the functionality of machine-learning systems is often associated with the high-quality size of datasets; however, repeated and recurrent problems, such as data bias during training, overfitting, and interpretability, continue to limit their wider usage. Furthermore, implementation of machine learning has become one of the highly demanded ethical issues in areas like healthcare and criminal justice, where additional attention is paid to the privacy, fairness, and transparency.[21]

A common wisdom says that Convolutional Neural Networks (CNNs) take control in recognition of images, and Recurrent Neural Networks (RNNs) are primarily successful in processing natural languages.

To perform satisfactorily in terms of machine learning (ML), there is usually a need to have access to high-quality and large datasets. However, there are still some fundamental challenges that hamper the wider use of systems such as bias in training data, overfitting, lack of interpretability and the associated processing cost. Other ethical issues continue to emerge in the world of high stakes whose field of application includes hospitals and criminal justice, and where privacy, fairness, and transparency issues should be carefully controlled.

Applications of Machine Learning in Artificial Intelligence

Machine Learning (ML) is one of the lower routes to achieve the Artificial Intelligence (AI) greater field. The ability of systems to deduce knowledge out of information, and perfect performance over time without being explicitly programmed, has dramatically changed various fields because of ML. Its usages currently include the medical, financial, motor transport, production, education, and other fields of knowledge, thus, encouraging smart decision-making and broadening automatization in disciplines.

1. Healthcare and Medical Diagnosis

Machine learning is commonly used in the diagnostic systems that diagnose pathologies, e. g., cancer, diabetes, and cardiovascular conditions by means of interrogation of complex medical data sets. Convolutional Neural Networks (CNNs) as one of the leaders among deep learning algorithms have demonstrated impressive results when analyzing radiographical and histopathologic images.[16]

2. Finance and Fraud Detection

Diagnostic workflow with machine learning has emerged as a pillar of detecting diseases referred to as cancer, diabetes, and cardiovascular disorders, through interrogating elaborate medical datasets. Conventionally, in the family of deep learning methods, the Convolutional Neural Network (CNN) proves to be especially effective in the analysis of radiology and histopathology images.[17]

4. Natural Language Processing (NLP)

The subfields of natural language processing most benefited by the use of machine learning (ML) are machine translation, sentiment analysis, and chatbots. Recent attention to transformer-based architectures, whose most popular representatives are BERT and GPT introduced recently, has significantly increased the capacity of the systems to understand the human language.[22]

5. Computer Vision

Machine learning forms a significant cornerstone in the context of computer vision as it provides systems of analyzing the real world visual data. Digital image classification, object detection, and face recognition as well as autonomous navigation, are based on convolutional neural networks (CNNs), which automatically generate hierarchical representations using pixel-level inputs hence the increased accuracy and scalability.[23]

6. Autonomous Systems and Robotics

Reinforcement Learning (RL), a subfield of ML, is extensively used in robotics and autonomous systems. Self-driving cars, for instance, utilize a combination of supervised learning for perception and RL for path planning and decision-making. These systems adapt dynamically to real-world environments.[24]

7. Cybersecurity

In machine learning (ML), reinforcement learning (RL) is a well-utilized subfield of research, mostly in robotics and autonomous systems. A particular example of this application is self-driving cars that normally combine the use of supervised learning on the perception tasks and RL in planning the path and making decisions to dynamically adapt towards the real world scenarios.[25]

8. Personalized Recommendation Systems

The last several decades have been characterized by the increasing prevalence of recommendation systems that are (and will continue to be) powered by machine-learning models and technologies. Techniques like collaborative filtering and matrix factorization query user behaviour to optimise the content delivery system hence developing the associated levels of user engagement and satisfaction.[26]

AI IN RADIOLOGY

Another adage, which is one of the most spread among radiology residents, implies that, the more the images are observed, and the more the examinations are reported, the better they are observed. This statement has its counterparts in the area of machine learning and, more specifically, deep learning. The radiologist has over the last few decades been reduced to an image analyst and interpretation of the findings has intensively been offered to clinicians who are outside the radiology sphere. It is dangerous such a situation as clinicians are skilled at the combination of radiological findings with the history of the patient and additional information but are not experts in radiology. Therefore, even though a clinician may have a specific period of time devoted to interpreting his or her imaging, the final meaning of a radiological examination is often determined by those who are not thoroughly trained in the field of radiology. Artificial intelligence in this case does not pose any sort of danger, but on the contrary, is an outstanding chance to improve radiology. In parallel to human cognition, with the help of AI algorithms, medical images are scanned, analyzing emerging trends once exposed to a huge body of research. Responsive systems of this type may provide conditional probabilities that may be used to guide Bayesian decision-making. It is a path which started with the projection images that were used in the early years of radiology like a radiograph or planar scintigrams to later to cross-sectional modalities like ultrasound, CT, tomosynthesis, positron emission tomography or MRI which progressively became more complex and voluminous in nature. Started in the 1930s but fully realised only in the digital age, the development to three-dimensional imaging now allows detailed anatomic representation and interrogation of functional status. The corresponding increase of information to be processed has revolutionized the radiological practice: the analysis has been replaced by expert methods of inferential interpretation with the pragmatic approach to detecting and describing abnormalities. The time taken to extract the data is too long; therefore, in such a situation, we will have to sacrifice other aspects of time, such as synthesis of clinical and laboratory situations.[27] In an attempt to restrict the radiologists to the analysis of the images only, the clinicians bear the ultimate effort of analysis of the radiological reports. This set-up is highly risky because, even though non-radiologists can say that they understand the context of the clinical situation, they have no expert radiological knowledge that informs a proper interpretation of images. Indeed, the lack of sufficient temporal provision of clinical judgement of the radiologist makes it so that goodness or badness of radiological examination can be misinterpreted by a non-expert in medical imaging. As a result, the good news is that artificial intelligence (AI) is not as such a threat to radiology, but it is a valid prospect of systematic improvement of it. The analogy of computer intelligence with the thought process of humans involves the systematic examination of medical images by AI systems to identify patterns within them after enormous training with huge data pools of exams. These systems have the ability of relating quantitative measures of structural specificity which is usually denoted in form of conditional probabilities, supplementing the usage of Bayesian inference in making decisions.[28] Artificial-intelligence has found its rightful place in modern medical practice, and radiology turns out to be among its key areas. This rise may be explained through three interconnected aspects namely availability of bulk digital imaging data, increased computational power and availability of radiological tests. At the same time, a sharp increase in workloads on diagnosis, in combination with an inadequate number of high-quality and well-experienced radiologists, has made AI an essential strategic priority. Responding to this, researchers have created image-processing and computer-vision systems which aim at streamlining the working of diagnosis procedures.[16] Pathological visualization is an important diagnostic value to a clinician, providing a steer towards an analysis of the disease that facilitates disease awareness and disease treatment formulation. The supporting technologies are still going on advancing the boundaries of visual depiction to more precise and interpretable form. The use of computational methods in imaging pathology is a new modern frontier, and the most common methodological options are deep learning and big-data analytics. These models promote the obvious display of the pathological features, optimize the diagnostic process, and, consequently, reinforce decision-making process. At the same time, the challenges of hardware, especially the use of increasing resolutions of the imaging sensors and quicker processing devices, are also playing their part in enhancing the histopathological visualization. The newly emerging advances, together, allow clinicians to examine pathological specimens with more accuracy and timeliness that eventually result in the best patient outcomes.,[29] alert emergency Alert events[30], It is a longstanding issue with regards to the lack of manpower availability in the healthcare sector; therefore, it is becoming eminent. When experienced professionals who have proved themselves in the workforce leave, aspects of supply and service provision are compromised at the same time, the quality of care will similarly be reduced. Such consequences are aggravated by the ageing workforce, the prolonged retirement age, and the labour market conditions that face the younger generations with more and more reasons to avoid pursuing their careers in healthcare. Even though there has been a wide range of policy interventions, their effectiveness has not been that good. In turn, it is necessary to develop new strategies.[31] Historically, radiologists have been involved in the role of visual inspection of medical images in their search of pathology through what can be termed as traditional processes of medical image analysis. As a result, investigations have been aimed at the development of computerized methods of calculation, which would enhance this line of professional work, but not replace it. The goals of research in this area are to recognize and excite features out of the human eyeballs visual definition along with providing the information in time interval that the human operators cannot do.[32] Radiology forms a critical part of medical diagnosis and treatment of various conditions as it offers medical practitioners with digital imaging of body organs internally, to aid diagnosis and planning of treatment procedures. Reading of medical imaging is however cumbersome and technical, at times requiring expert knowledge and a lot of training. Over recent years, artificial intelligence (AI) has taken centre stage in the field of radiology by providing new opportunities when it comes to improving accuracy, efficiency, and patient outcomes. ChatGPT, which is also a large language model built by OpenAI to learn using natural-language processing (NLP) to analyze and interpret medical images, may be one of the most promising medical-image diagnosis tools based on AI.[33] Radiology forms a critical part of medical diagnosis and treatment of various conditions as it offers medical practitioners with digital imaging of body organs internally, to aid diagnosis and planning of treatment procedures. Reading of medical imaging is however cumbersome and technical, at times requiring expert knowledge and a lot of training. Over recent years, artificial intelligence (AI) has taken centre stage in the field of radiology by providing new opportunities when it comes to improving accuracy, efficiency, and patient outcomes. ChatGPT, which is also a large language model built by OpenAI to learn using natural-language processing (NLP) to analyze and interpret medical images, may be one of the most promising medical-image diagnosis tools based on AI.[34] Based upon empirical evidence, with the further development of radiology research and concrete use cases of artificial intelligence in the clinical scenario, the introduction of artificial-intelligence (AI) systems within the radiological field is likely to critically transform the field of radiology.[35] In the case of Guyana, a country whose population is comprised of a little more than 750,000 citizens, with no indigenous radiology residency programs, RAD-AID was able to supply much-needed support by establishing these postgraduate training programs on Guyana soil and concomitantly integrating AI-related curricular units because of a growing urgency in the need to reduce the time required to render an analysis of significant amounts of radiological data.[35] Deep-learning-based diagnostic systems have shown diagnostic parity with, and in other cases even surpassing performance of human experts in some fields. Among others it is possible to note lymph-node metastasis finding and mammography malignancy finding.[36] The modalities based on AI prove to have significant ability to segment meningiomas during MR imaging. A study by Laukamp et al. used a multi-parametric deep-learning architecture to work on preoperative MRI data sets and with detection and segmentation performances up to the level under the manual detection and segmentation of two radiologists. The research considered a training group consisting of 249 cases of MRI, which were annotated with the BRATS benchmark and a total sensitivity of 55/56 against gliomas was recorded in the validation phase. These findings point to the clinical value of AI-assisted workflows and report optimistic implications of radiological automation in the future.[37]

AI in Oncology

Machine learning is a branch of AI, now found everywhere in the scientific and social world, in clinical trials, robotics, self-driving cars. Its practicality in the medical field is best illustrated in the outstanding role in the Human Genome Project and those involving Cancer Omics including The Cancer Genome Atlas[38], Three projects can be pointed out in the modern environment of cancer research: the International Cancer Genome Consortium, the Clinical Proteomic Tumor Analysis Consortium, and an array of international machine-learning challenges managed by the DREAM Challenges. All of these organisations have made their contribution to the field in different ways, but they all made its course aimed at the more data-driven direction.

To begin with, the International Cancer Genome Consortium (ICGC) has been engaged in a concerted attempt to catalogue the molecular landscape of several types of tumors in different kinds of population. via its systematic sequencing program, ICGC has created a huge amount of data that covers four different modalities of cancer, genomes, epigenomes, transcriptomes, and methylomes, across close to twenty types of cancer. These data are freely available hence resulting in a resource of wider research community.

Then there is the Clinical Proteomic Tumor Analysis Consortium (CPTAC) which focuses on proteomics on translational level where large-scale profiling of the proteome is performed to provide answers on the Tumor heterogeneity and to translate molecular knowledge to clinical use. Using mass-spectrometry-based proteomics, CPTAC has produced large cohorts across multiple tumor types and stages, has charted histo-proteomic profiles, and now making formal recommendations to clinical pathology laboratories.

Lastly, an iteration of one of our DREAM Challenges iterative, community driven, competitions that tap into crowdsourcing and crowd validation, can also be used in machine-learning-based inquiry in cancer research. The problem spaces that have been addressed by these competitions are cancer prediction, response prediction to neoadjuvant therapy, detection of residual tumours, prediction of chemotherapeutic toxicity and they are using databases matched with clinically or biologically annotated data. Through institutionalizing this style of open collaborative workflow, the DREAM Challenges have indicated that mass participatory analytics can be used clinically productive in the investigation of cancer.[39] The recent formation of extensive data sets with the focus on medical treatments and outcomes has great potential of relegating the field of oncology to the status of a data-driven, outcome-focused domain. Initial use of machine learning in diagnostic and therapeutic settings has shown promising results in detection of breast cancer through x-ray images, and thus provides evidence of concept of wider use of machine learning in the cancer continuum[40], new antibiotics finds[41], The aim of the research was to investigate the possibility of prospective identification of gestational diabetes mellitus based on electronics health records. To this end, longitudinal data was retrieved through electronic health record system of one academic medical centre including the pre-pregnancy, antenatal and postpartum periods. Within those data, there were more than 160 000 women who delivered eventually between 2011 and 2016, and these data were used to create the predictive models. Analytic techniques entailed refinement steps of logistic regression variations until the ultimate model had five predictors that showed an area under the curve (AUC) of 0.715. Age, body-mass index, past history of gestational-diabetes, parity and püreria status were these predictors. Classification of this model on cases was precise, where it predicted 83.2 % of cases compared to the random 50 %. It is well to note that the performance in the model was based on a cohort where the glycemic profile of the women was diverse; with this in mind, it is easy to generalize the results to the general group of pregnant women[42], A molecular fingerprint of response to treatment is a fixed expression of genes which determines clinical outcome, especially effectiveness of drug therapies. Such signatures are applicable to stratify patient cohorts into subgroups of phenotypically similar patients so as to have a closer definition of therapeutic responses. Through the use of personalized medicine approach, clinicians are capable of using such knowledge in the process of steering personalized treatment decisions. This way, treatment on the evidence-based medicine principles could be easier to identify to treat patients with precision therapeutics via the identification of these signatures.[43] Evidence-based medicine (EBM) scoring systems are being used more and more in cancer care to assist with risk assessment and diagnosis, prognostic staging, treatment selection and long-term monitoring. Many of the systems were developed as clinical observations based on light microscopy but grew with increasingly complex procedures, such as gene expression assays, and next-generation sequencing of somatic and germline genomes. This leads to a growing list of prognostic and predictive factors of each type of disease as we can find increasing prevalence of Genomic-informed versions of clinical models.[44] Even though adding additional predictors has the potential of enhancing the explanatory power, it also increases the complexity of the models as well as creating interactions webs that cannot be deciphered using familiar interpretation technologies, but in most cases, augmentation will expand the resolving ability of the resulting modelling algorithms.[45] Implementation of artificial intelligence in prediction of anticancer drug activity, or in advancing anticancer drugs has been reported. It has been shown that unique tumours may display unique drug-response phenotype even when identical agents are employed. The associations between the phenomenon of cancer-cell genomic heterogeneity and drug-response outcomes can further be identified with the help of the data retrieved through high-throughput screening.[46] A machine learning approach was created to combine the cancer-screening data and develop a random forest model. The model allows predicting anticancer drug behaviour, depending on the presence of mutations in the genome of the cancer cell.[47] Applying machine-learning algorithms, the investigators will be able to quickly analyse their mechanism of developing resistance to drugs, thereby contributing to the development of cancer treatment and decisions about using drugs in treatment and clinical practice.[48] The research of Somashekhar et al. demonstrates that the ML systems can achieve the performance at the level of experienced specialists in the assessment of malignancy to diagnose breast cancer, which signifies the opportunities of AI-based solutions in the diagnostic staging of breast cancer.[49] Watson underwent prospective, double-blinded validation in which the concordance rates were 93 % with an expert multidisciplinary tumour board with regard to the recommendations of breast cancer treatment. Similar results had been recorded by Bejnordi et al in an even later study.[50] In a prospective study of 129 histological patient slides (49 with lymph-node metastasis, 80 without), these histological slides were evaluated by 11 common pathologists, and the diagnostic accuracy of an AI algorithm was compared with each pathologist. The algorithm displayed a higher diagnostic measure and the 30 hours spent by pathologists on the interpretation of the slides was a considerably higher waste of time compared to the imagined immeasurable run time of the algorithm.

As regard to the analogy of lung cancer, there are available evidence that AI performs better as compared to human observers. Using 2186 stained histopathology whole-slide sets of lung adenocarcinoma and squamous cell carcinoma data as test-set, Yu et al. demonstrated that AI solutions were more accurate than their human counterparts in the diagnosis of pathology.[51]

Improvement in artificial intelligence (AI) has made it possible to extract a relevant reference within a short period, regardless of the size of the data. At the same time, deep-learning convolutional neural networks (DL-CNNs) provide the ability to infer the patterns of medical literature, thus contributing to the accuracy of medical diagnoses and the choice of most appropriate methods of treatment. The review explains AI comprehended applications that emerge in paediatric oncology research.[52]

The role of artificial intelligence models for detecting breast cancer

The diagnosis plays a critical role in the success of the management of breast cancer and the application of artificial intelligence in screening mechanisms, especially when inspecting biopsy slides has shown to improve treatment options. Due to the advancement in the area of diagnostic accuracy, scholarly interest increased in this area in recent years. Artificial intelligence seems to be an interesting solution to breast cancer detection. Computerised radiology has taken a leading position in the wider scenario of medical imaging, in that it helps in the early detection as well as analysis of tumours. Computational processes, computer vision, lesion detection, and pattern recognition are among the processes that have been dependent on the discipline to reduce image analysis complexity. Computational radiology is designed to enhance the diagnostic efficiency and accuracy by automating the operations traditionally performed by human specialists. It involves thereby the derivation of medical images imaging biomarkers, which would, in turn, furnish quantitative representations on the basis of which the therapeutic responses get modelled and in giving the potential prognostic and predictive information. The two stand pillars of artificial intelligence namely, machine learning and deep learning act as pivotal mechanisms in detecting breast cancer. Large sets of medical imagery are used as the core data on which machine learning models are trained, which afterwards generalise descriptive patterns, and enables the automatic analysis of new image data.[52] Deep learning is a branch of machine learning based on artificial neural networks, with主NN pour fouled by several dozen layers of variables, used to automatically learn hierarchical features of a given data set. Its understandable exploitability in fields like picture taxonomy and the acknowledgment makes it a highly useful procedure in diagnosing breast carcinoma.[53] Artificial intelligence (AI) has taken a significant step in the field of screening of breast cancer, and object detection (segmentation) and classification of tumors are its main activities. These abilities support breast cancer screening with the help of AI (Tran et al., 2021). An idea of the progression of AI in the health-care system is depicted in the schematic diagram, as shown in Figure 3.

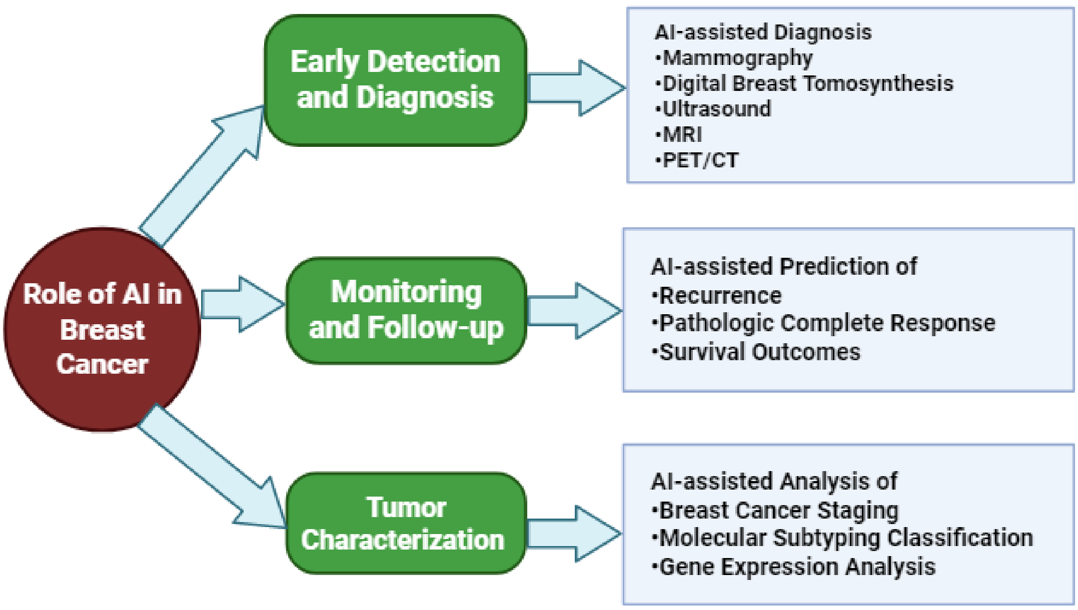


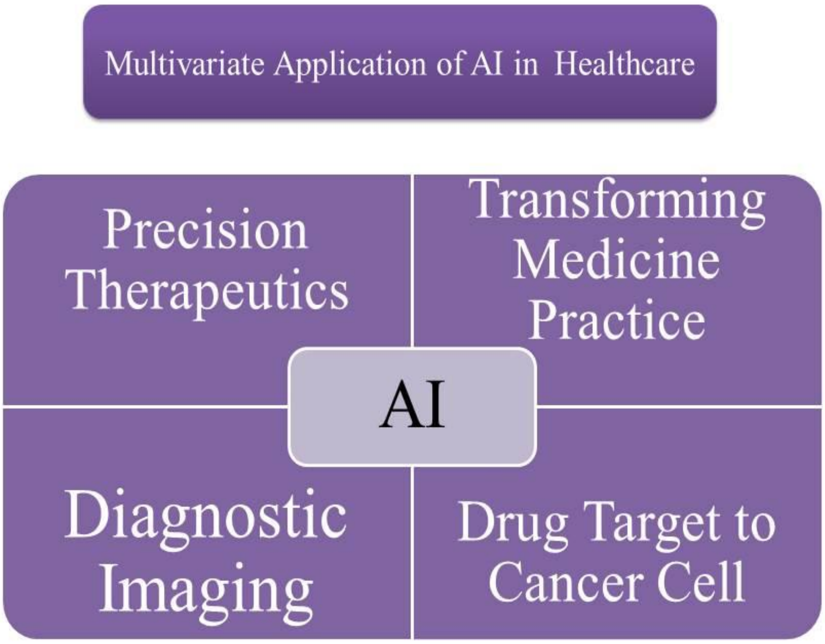
Figure 3: Describes main areas of artificial intelligence (AI) application in the treatment of breast-cancer. The ability to detect and diagnose at early stages depends on AI using imaging modalities as one of them, such as mammography, ultrasound, magnetic resonance imaging (MRI), and positron-emission tomography/computed tomography (PET/CT). During the surveillance, it engages ability to foresee recurrence, therapeutic response, and survival of the patient. It also enhances tumor composition by the use of staging, molecular subtyping and gene-expression profiling.

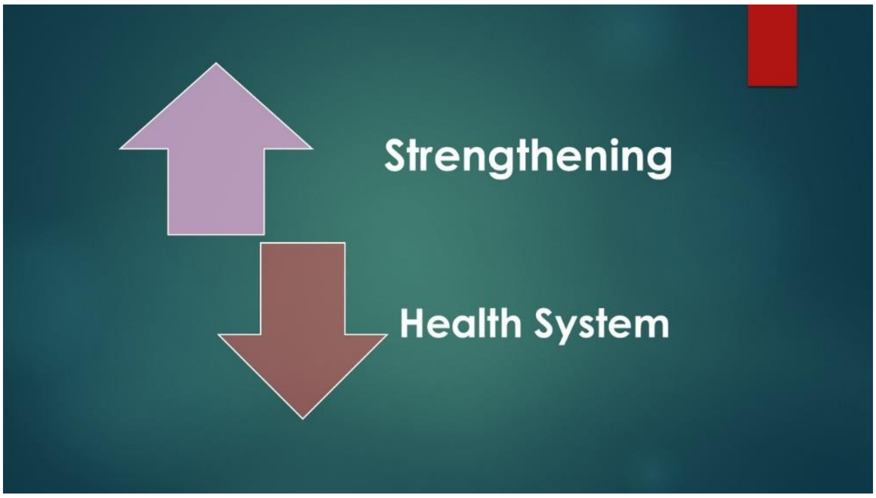
Artificial intelligence (AI) finds a wide variety of applications in breast cancer (BC) imaging, its automation of screening and diagnostic work, description of lesions, and even forecasts of treatment success. In the proceeding discussion, the framework discussed in Figure 4 can be related with and exists to survey the currently available variants of AI techniques in these regards.

Screening and Diagnosis AI has the promise to accelerate the BC screening and diagnostic pipelines by conducting a triage on originating screening tests and triaging patients to referral. Current workflows normally include interpretation of multiple imaging modalities, which are acquired using diverse areas of expertise, hence the existence of a collective framework that would help in synthesis of all the modalities provides potential. Currently established techniques are usually based on either convolutional neural networks (CNNs) or similar networks to derive spatial and contextual characteristics out of patient data. Even though such systems are highly accurate, operational restrictions, including long processing times and the need to process large, curated datasets, are still the barriers to implementation.

Lesion Characterization Using AI, lesion characteristics can be charted, which would be critical in making diagnosis and treatment decisions. The existing methods include extracted feature sets which are passed to machine-learning classifiers. The chosen features represent typical appearance measures, their geometrical morphology, and texture details, etc. These systems show similar or better overall diagnostic performance compared with manual evaluation, in addition to having better observer-to-observer reliability. However, their resilience to domain shift, i.e. to changes in population or imaging protocols has not been adequately tested as yet.

Treatment Outcome Prediction Predictive modelling provides prognostic data which forms a basis of clinical management. The existing prediction models involve using the classical types of statistical analyses, logistic regression, and random forest, which are enhanced with radiomic features retrieved using preoperative imaging. The accuracy of such systems in predictive performance is comparable with the manual expert assessment that reflects the benefit of radiomics-based models to predict positive or negative outcomes. Effectiveness however depends on availability of strictly curated data sets and performance can decline on extrapolation to an unknown population.





AI REVOLUTION

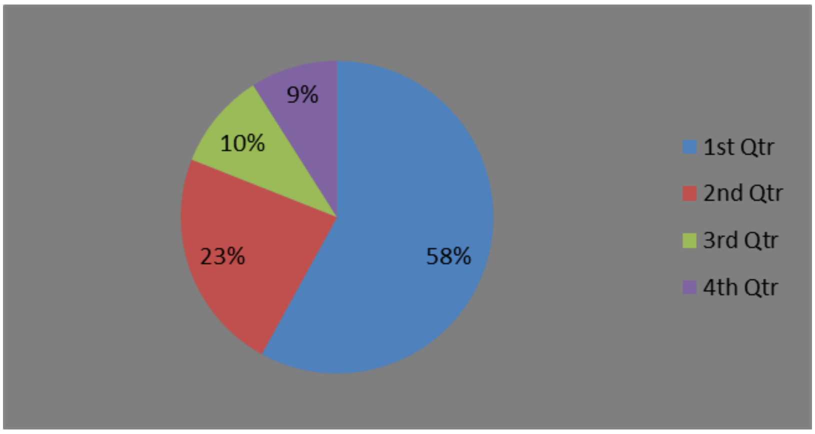


Figure 4: Comprehensive Contributions of Artificial Intelligence to Healthcare in Connection with Professional Development and Healthcare Processes

The application of AI in medical imaging has seen a significant growth over the past couple of years[54] especially in the breast imaging segment.[55] It is a trend that can be explained by multiple mutually reinforcing factors: the explosive growth of affordable computational resources (and, as a result, access to cloud-computing infrastructure), which underpin the ability to support billions of operations per second; the abundance of digital data; and a fairly low cost associated with the ability to store digital data. Artificial intelligence AI is a broad sub-discipline in computer science concerned with engineering systems that exhibit goal-oriented behaviour, which would enable them to perform (and/or achieve) tasks demanding intellectual capabilities similar to human intelligence, such as judgment, learning, and problem-solving. There are various methodological frameworks comprised in this field, with machine learning (ML) and deep learning (DL) being among the most notable ones. Artificial intelligence technologies are integrated across the modern culture and can be found in a variety of gadgets that can be personal computers, cell phones, smartwatches, and even cars. They are also equally diverse in their usage which includes filtering junk email, running robotics applications, and voice-processing applications through to providing clinical decision support systems. Computer-aided detection/diagnosis (CADe/CADx) tools based on conventional ML tools appeared in the 1990s.[56]

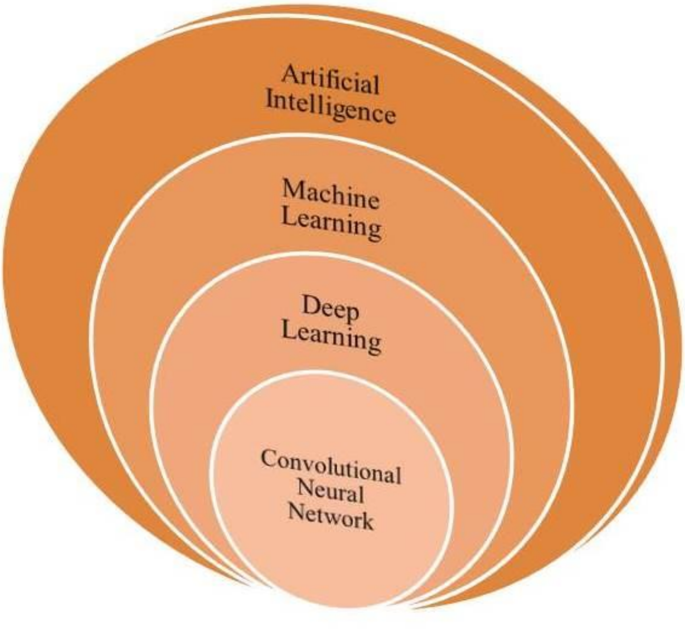


Figure 5: Intelligence can be viewed as a multi layered schema, where the upper layers stay on the foundations of the lower layers as neural-phone network architecture. The first layer is the cognitive domain that includes both human and machine intelligence, the second layer is intermediate representation of the cognition domain and the third layer is the actual neural network implementation, e.g. convolutional neural networks (CNNs). The output of one layer is transferred to other layer (forwarding) in this schema and the entire system is used in a iterative manner through feedbacks and simplification.

AI IN CARDIOLOGY

Artificial intelligence and generalised machine learning methods have increased the rate at which clinicians read and diagnose cardiovascular data. Current electrocardiographic techniques allow the interpretation of it signals to be automatic, and three-dimensional imaging in echocardiography provides real-time measurement of cardiac performance. SPECT Myocardial perfusion study also has the capability to provide automated segmentation and perfusion perfusion analysis and cardiac computed tomography angiography used in the measurement of coronary calcification does not require measurement values to be taken manually. Similar advantages are the hallmarks of a cardiac magnetic resonance imaging, the latest version of which provides an automatic segmentation in addition to the quantitative perfusion and flow measures. The modern cardiologist is thus left to process a combination of multimodal image data sets, and the stage of first interpretation most often either becomes carried out visually guided to score the data or just automatically achieved through a quantification procedure that makes possible the accurate diagnosis and risk stratifications of patients.[57] The application of artificial intelligence (AI) in cardiovascular fields has seen its great growth in the past 10 years. The AIs now carry significant roles in the investigation of the diagnosis, segmentation and reconstruction, therapeutic guidance, disease prediction, and procedural planning based on images. The following discourse looks into some of the cardiological assistance applicative forms: interpretation of electrocardiogram (ECG) trace, analysis of medical images, use of digital health notes, and offer of automatic clinical thought processes.[58] Medical imaging over the past years considered the usage of artificial intelligence (AI) algorithms to diagnose an image, segmentation and reconstruction of an image, quality control, prognostication of a patient, phenogrouping, and scientific insight gathering. Demographic data (age, sex, etc.), comorbidities present in each patient has been utilised to maximise the performance of machine-learning (ML) models. At the same time, the AI-based software systems and risk assessment tools also found their use within the sphere of cardiology.[59] In the field of AI-powered cardiology, algorithms design is being an ultimate modulator of CDSS clinical decision support systems. The traditional CDSS usually apply rule-based systems with the clinical knowledge being expressed as clear statements of a procedure. With the formation of machine learning, on the contrary, a change of the conceptual and operational level occurred. The paradigms established in supervised learning, mostly the Support Vector Machines and Random Forests, resemble the predictive machinery that operates on the, now historic, data of either populations or patient cohorts and, in contrast, unsupervised learning applications, such as clustering predictors, can be instrumental in defining the patterns of patient subgroups and disease predispositions. All these collectively have re-align the paradigm of CDSS and in the process have enhanced the diagnostics of clinicians.[60] In current medical imaging, convolutional neural networks (CNNs) became a potent tool in improving the diagnosis accuracy especially when it comes to cardiovascular imaging. With these technologies becoming more mature the issue of transparency and interpretability in AI aided decisions takes on a new importance. Explainable AI incorporated in clinical decision-support systems (CDSS) provides a system to explain the outputs of complex models. Many different decision trees, marked by clear decision paths, along with model-agnostic models, e.g., LIME, have explainable interpretations of individual predictions. This kind of explainability will foster professional trust and allow aligning of the AI-based suggestions with clinical experience.[61] In cardiovascular medicine, artificial intelligence (AI) is expected to achieve three purposes: the improvement of patient care, the optimisation of clinical workflows and the general enhancement of clinical outcomes. The current development in the sphere of patient data acquisition, the heterogenization of diagnostic equipment, and the generation of new treatment mechanisms in cardiology make the field especially well-placed to utilize the power of AI and its consequences.[62]

The supported evidence points to the fact that a quite simple clinical intervention, such as electrocardiography (ECG), may produce large data sets, and artificial intelligence (AI) may transform the data into a clinically relevant and strong tool to predict risks.[63] Inclusion of AI-based tools in the field of cardiovascular imaging is expected to work in the direction of improving reliability and quality of everyday clinical decision-making. Incorporated directly in all parts of the imaging spectrum, ranging all the way through acquiring an image to the final reporting phase, AI has had substantial impact on every steps of the cardiovascular imaging workflow.[64] The past few years were extraordinary in terms of the development of artificial intelligence (AI), which affected all the phases of the diagnostic workflow in a significant way. It is important to note that the effect has been felt considerably in computed tomography (CT) and magnetic resonance imaging (MRI).[65] Today, the practice of introducing the artificial intelligence (AI) into medical graphic is restricted to some local solutions, i.e., detection of pulmonary nodules on chest computed tomography. A more holistic evaluation of the potential of AI is not certain, and a more generalized evaluation of the use of AI in cross-modalities needs to be enacted. The example of the Echocardiography is also a good test case as this procedure is widely used and has a great variety of clinical possibilities and has a well-established workflow.

In order to come up with the level of the AI influence, a thorough pilot study was conducted. We retrieved images of one institution integrated clinical information system in terms of both of diagnostic and therapeutic echocardiographic examinations. The AI-based platform was based on a convolutional neural network using which it was possible to segment the myocardium and left ventricle. Segmentation outputs were compared to manual measurements made by an experienced examiner with automatic measurements. The agreement of the automatic with the manual measurements was assessed on intraclass correlation coefficients.

The findings represented good agreement between machine and hand calculations with intraclass correlation coefficient of 0.72 to 0.90. Automated measurements established a good correlation with known values of reference ranges and it was possible to extrapolate reference intervals to this AI-based pipeline. The root mean squared error in measurements of left ventricular end-diastolic diameter, left ventricular end-systolic diameter and left ventricular volume was less than or equal to 5 percent.

To sum up, the findings of this pilot endeavour indicate that AI-based algorithms of segmentation and measurement in echocardiography are capable of producing precise volumetric and dimensional parameters, which agree with traditional norms. These results considerably confirm the application of AI in the imaging field and allow the future prospective studies to be conducted on its validity[66], In their research, Barry et al. (2022) adopt a systematic review approach to trace how long-term nitrogen-containing psychological medication was reported by its recipients. Yet, the authors focused their research on the analysis of ten qualitative papers to clarify the outcomes of prolonged exposure to these approaches. The results of their research findings are that in spite of the heterogeneity of the self-reported findings, some themes were repeatedly identified in all studies. These themes consist of both praise and criticism of the further use of medication. On the one hand, the participants mention stability and freedom of the symptom burden regularly, and on the other hand, they cite the costs of medication, side effects, and concerns about dependence.[65]

To draw a knowledgeable prediction of potential of the domain of artificial intelligence in the future, it is necessary to question its prevailing gap and limitation. The given endeavour will shed light on future patterns of progression. The current literature describing the use of AI in the field of echocardiography demonstrates such dynamic: almost all publications up to date use retrospectively acquired data and study how their system performs in diagnostic operations with the use of discrete tasks, most often, small-scale and exploratory in nature[67] To draw a knowledgeable prediction of potential of the domain of artificial intelligence in the future, it is necessary to question its prevailing gap and limitation. The given endeavour will shed light on future patterns of progression. The current literature describing the use of AI in the field of echocardiography demonstrates such dynamic: almost all publications up to date use retrospectively acquired data and study how their system performs in diagnostic operations with the use of discrete tasks, most often, small-scale and exploratory in nature.[68] Modern studies are underlining the need to conduct future studies in which the consideration of clinical feasibility of AI algorithms is applied to the cardiovascular realm.[69] Under modern rhetoric, one of the preoccupations relates to the conditions under which the machine output has dissimilarities with human evaluation. Therefore, critical testing of algorithm functionality ensues. The clinical judgement of the physician is essential but it must be realigned such that the use of artificial intelligence is to complement and not to supplant the thought processes of the human mind.[70]

MATERIALS AND METHODS

To facilitate the narrative review of the field, a systematic search of literature was performed using PubMed, Scopus and Google Scholar. The search protocol aimed at synthesising the evidence that exists with regard to the use of AI in management of cardiovascular diseases. An extensive set of search terms was utilized, and they were as follows: environment, artificial intelligence, cardiovascular disease, heart disease, machine learning, hypertrophic cardiomyopathy, hypertension, coronary artery disease, primary pulmonary hypertension, heart failure, atrial fibrillation, anemia. Related articles were defined and those others that were not designed as cases were discounted, editorials, letters or those that do not give English translations were also discounted. The last search has been made on 30 August, 2023.[71]

Coronary artery disease

Betancur et al.[72] The purpose of the present study was to train a deep learning (DL) model to predict coronary artery disease (CAD) CAD, to be more exact Future CAD) based on stress SPECT myocardial perfusion imaging (MPI). A group of 1638 patients without CAD, who were subjected to stress SPECT MPI, and underwent invasive coronary angiography that was carried out within 6 months of MPI. The model was tested through stratified tenfold cross-validation, and the area under the curve (AUC) of CAD predictive model was 0.80 per patient and 0.76 per vessel, meaning that DL can improve MPI analysis and make future CAD prediction more sensible. Moreover, such findings denote that MPI facial features can be linked to high incidences of certain ailments.[73] Currently, an opportunity to diagnose pathological conditions based on facial features is possible due to the deep learning (DL) method[74] Lin et al[75] In the current research, it was investigated how a deep-learning framework can be successfully used to detect coronary-artery disease (CAD) based on face photographs of 5796 patients automatically. An independent test cohort of 1013 subjects were used to assess the prediction ability of the model. This algorithm provided an AUC of 0.73 and the CAD detection accuracy value of 68 per cent. The findings denote that in case the necessary size of the dataset is achievable, DL-based diagnostic strategies can be helpful in screening the disease.[76]

AI IN GASTROENTEROLOGY

With the rapid surge of artificial intelligence in medicine, the clinical implications of AI in medicine are emerging.[77] Using endoscopic and radiologic imaging as a primary source of data, gastroenterology has emerged as an appealing field for AI application. Particular attention has been focused on several aspects such as neoplastic lesions of the gastro-intestinal tract detection to speed up calmative procedures; limit a frequency of diagnostic mistakes; standardize image quality; limit inter-observer discordantities in visual rating; and radiological and histological interpretation.[78] The potential of AI in gastroenterology: has been demonstrated by the excellent body of ML study with respect to image recognition. These algorithms have already been leveraged for endoscopy with promising results, and consequently have the potential to enhance the disease detection and classification in a manner better than the most seasoned endoscopists.[79] Yet, several challenges, such as the discovery of biases in the algorithm, the extension of generalizability, and the enhancement of interpretability remain.[80] Furthermore, for these new innovations to be truly disruptive to health care, they must obtain broad utilization. An important level of scepticism does prevail in the medical fraternity about the potential of the AI in the clinical world which will need to be amicably settled in subsequent years.[81] There has been an immense development in the field of gastroenterology. As the incidence of gastrointestinal (GI) disorders, including inflammatory bowel disease (IBD), colorectal cancer (CRC), and a number of functional GI disorders, continue to grow, there is an urgent demand of convenient diagnostics, and patient-tailored treatment approaches.[82] The obstacles to effective care are associated with complexities of ways to diagnose, clinical practice variations, and human cognitive capacities that bring about mistakes.

Here Artificial Intelligence (AI) and especially its subsets, machine learning (ML) and deep learning (DL) have emerged as a breakthrough to deal with these complications. The impact of AI technologies on the healthcare industry is translated to the field of gastroenterology where the way healthcare providers approach the issue of diagnostics, treatment plans, and the management of patients is changing. Through automation of repetitive processes, delivery of superior data analytics, and improvement of diagnostic performance accuracy, AI is laying a foundation that it can be integrated into daily practice.[83] In gastroenterology, AI is being experimented with outstanding outcomes in how to diagnose imaging research techniques, including ultrasonography, computer tomography, magnetic resonance imaging, and yet not in the least in endoscopy, capsule endoscopy and in biopsy and subsequent digital pathology analysis.[84] The adoption of the available options of the above listed methods of diagnosis and the results analysed by blood tests enables the AI systems to take over the whole process of medical care in condition to deliver the following outcomes: detection, diagnosis, classification, staging, treatment plan, evaluation of the risk of surgery, prognosis prediction, prediction of treatment response, prediction of risk of metastases, monitoring of follow-up, prediction of the disease progression, of complications and customized targeted therapy delivery feature.[85] The implementation of AI-based systems is already applied in endoscopy, the detection of neoplasia, identification of gastrointestinal bleeding, and the detection of polyps.[86] More, diagnosis of liver fibrosis, fatty liver disease, hepatic focal lesions, and evaluation of liver cirrhosis is done by use of AI technologies. There is gold standard, which is pathological analysis in the areas of gastroenterology and hepatology to find out the cause of sickness. Due to the shortage of pathologists in the whole world, the correctness of pathological analysis is declining. As the whole-slide imaging scanners and AI based technologies are advanced medical costs can be reduced without reducing the accuracy of the diagnosis.[87] However, there is an upsurge in artificial intelligence (AI) application in endoscopy as a way of helping clinicians on different parts of the procedure. Endoscopic images can be analysed through AI algorithms as the algorithm can analyse images and provide guidance to the clinicians regarding a possible area of concern and help find abnormalities.[88] This can enhance the accuracy of the diagnosis and low chances of overlooking any abnormalities. The devices made in AI can be programmed to see patterns and abnormalities in endoscopic images that are not easily noticed by the human eye. This may assist the clinician in an effort to discover areas of concern that might not have been detected in the first examination. It is also a possibility that AI could be useful to real-time analysis of videos in the case of endoscopy and help in early-stage cancer detection as well.[89] The gastroenterology diagnosis and treatment are founded on the flexible endoscopic image of the stomach duodenum and colon. Patient care requires early diagnosis of cancer and hence screening regimens are practiced globally. To increase the detection during a clinical exam that can take only a few minutes of time, and is conducted several times a day an AI based system was formed.[90] The CADe (computer aided diagnosis system) is used in staring the abnormal appearance on the screen by pointing out the area of abnormality to the endoscopist. Once the attention has been drawn towards the irregularity the CADx system manages to specify the endoscopic images further to a real time proposed diagnosis after switching to NBI (narrow band imaging) view.

The CADe was exhibited with 94 percent of colonic polyp detection rate.[91] This paper is an excellent source of evidence of how the gap existing between trained endoscopists and less trained endoscopists in terms of accurate and faster diagnosis can be filled using AI based platforms. CADx system demonstrated an ability to identify early gastric cancer and colonic cancer in endoscopy. It was also proven that it had a precision of 96.3 percent in identifying early gastric cancers with a sensitivity rate of 96 percent and specificity rate of 95 percent.[92]

AI IN OPHTHALMOLOGY

Ophthalmology has fared well because it relies on image-based clinical care and research as artificial intelligence (AI) technologies emerge.[93] Ophthalmology has fared well because it relies on image-based clinical care and research as artificial intelligence (AI) technologies emerge.[94] In the recent past, a large population of AI researchers in ophthalmology have employed the use of medical images in building a deep learning model to carry out high dimension analysis. They have been applied to perform screening and diagnosis of the most common vision threatening diseases with matching expert diagnosis performance, such as diabetic retinopathy (DR)[29], It can identify glaucoma[95], age-related macular degeneration (AMD).[72] cataract and other disease of the anterior segment[96], with precision. With deep learning technologies entering their maturity, scientists begin to attempt to work on disorder detection outside of the scope well-known to date (namely early-stage)[97], and prognosis prediction.[98] AI has demonstrated success on helping to diagnose and forecast many eye diseases. A number of studies have built DL algorithms based on retinal fundus images to realize referable DR with high level of accuracy. As an example, De Fau et al also developed a DL system able to diagnose referable DR and diabetic macular enema (DME) in OCT scans with sensitivity and specificity similar to retina specialists.[99] In their study, Burlina et al designed a DL algorithm based on more than 130,000 colour fundus images whose accuracy was 91.6% in a test to detect moderate and advanced age-related macular degeneration (AMD).[100] Grassmann et al trained a DL algorithm using 120, 656 fundus images, which had the accuracy of 94.3 to differentiate early and late AMD.[72] The innovative way the Artificial Intelligence is being integrated into the field of ophthalmology creates new prospects of the comprehensive ophthalmic clinical services.[101] With the extended life expectancy world worldwide, the age-related eye diseases also grow and this fraction already overstretches the healthcare system that cannot cope with new requirements yet.[102] With the assistance of AI, vision loss in patients can be detected at an earlier stage and thus results in maximizing healthcare shift in available resources by making precise forecasts and individual responses.[103] Artificial intelligence lends itself to ophthalmology where there are many digital methods including colour fundus photography, optical coherence tomography (OCT) and computerized visual field (VF) testing and very large databases these therapies offer.

Besides this, the world is increasingly experiencing life expectancy, coupled with occurrence of eye diseases, which could result in blindness due to preventable injuries to the eye ball.[104] There is already quest to create solutions to early diagnosis and treatment of these diseases, more so in zones where preferred access to doctors is a challenge. A variety of eye diseases are being developed using artificial intelligence especially diabetic retinopathy (DR), age-related macular degeneration (AMD), glaucoma and retinopathy of prematurity (ROP) which are some of the leading causes of sightloss.[105] One in every four people who have diabetes, i.e., 38 percent of the 400 million in the world, develops diabetic retinopathy (DR). This condition afflicts the small blood vessels that feed the retina and these can result in haemorrhage or retinal detachment resulting in impaired vision and blindness.[106] The American Academy of Ophthalmology proposes the screening of such immense number of patients to diagnose DR at its early stage.[107]

The use of AI, deep learning, and diabetic retinopathy diagnosis has been demonstrated to be effective in its early diagnosis. In their research Gulshan et al. trained on ten validation sets with 9963 and 1748 images and discovered that the sensitivity and specificity of their work was high in comparison to seven expert board-certified ophthalmologists. It can be concluded on the basis of this research that deep learning in ophthalmology can play an important role with regard to detecting diabetic retinopathy and macular enema by using retinal images, but it also requires further research.[29] AI has been used in ophthalmology to reduce the burden of disease like diabetic retinopathy (DR), age related macular diseases (AMD), cataract and glaucoma. The main cause of blindness and inability to see in the working age people men and women in the United States is DR, the other common causes are cataract and glaucoma as global causes of blindness. These are the very broad range of the commonality of the diseases and the access of imaging that makes them of interest in the application of AI-based methods. Such applications have been made on the basis of the large data sets (big data) which have been garnered by this extensive imaging. When paired with AI big data enables the identification of associations that are less pronounced and would not have been identified using less robust data sets.[108] In ophthalmology, machine learning and deep learning solutions have been the most extensively investigated due to the widespread access to non-invasive, fast and relatively low-cost ophthalmic imaging. Such developments in ophthalmic imaging have established the bulk of data needed in successful use of computer vision developments.[109] Another reason why ophthalmology is uniquely positioned to have big data questions is the Intelligent Research in Sight (IRIS) Registry, the world largest clinical database that is currently led by the American Academy of Ophthalmology.[110] Both AI and big data research operate on the data rather than through the accepted observation-to-hypothesis paradigm and hence enables discoveries that were not known within the conventional paradigm of research. Examples are of novel biomarkers among multiomics data7 microscopic relationships which could not be identified with the lower magnitude data,[111] and detection of imaging characteristics that were otherwise invisible by the naked eye e.g. the hyporeflective outer retinal band that is related to rod-mediated impaired dark adaptation and is a known indicator of early age-related macular degeneration.[112]

Glaucoma

Being one of the causes of permanent blindness, affecting more than 70 million individuals globally, glaucoma is an eye disease that is accompanied by the cupping of optic discs and impairments in visual fiNlL. Most vision loss can be avoided by early detection via timely treatment of glaucoma. Nonetheless, it comes quite late to notice such a type as primary open-angle one, normal tension, and chronic primary angle-closure glaucoma. Such types of glaucoma are painless, hence early stages of visual defects are timid that make the patient realize this condition during an advanced stage when the patient has already lost central visual acuity. Traditional glaucoma screening techniques also include optic disc and retinal nerve fibNr layer examination using specialists, thereby making them time consuming and labor intensive, thus, not suitable in mass screening. AI bffN nordicating the use of AI in cbst래 o governments around the globe to achieve greater screening and early detection of glaucoma by using automatized explanation of fundus and OCT images.[113] The AI systems have managed to identify glaucomatous optic neuropathy with high sensitivity and sjNcificity togetNher dramatically increasing the NfficiNncy of screening programs. Differing with the two-dimensional fundus imaging that acquires two-dimensional images of the optic nerve head, OCT is able to depict a three-dimensional optic nerve head structure which can identify depth-resolved structural alterations of glaucoma. Organization of OCT AI models on OCT images has been found more accurate than AI models trained on fundus images and their level of accuracy comes close to that of glaucoma specialists. The progression of glaucoma can also be foreseen using AI that analyzes the visual fiNlL data and detects the progress of the disease earlier than the conventional methods do. The innovations in AI technology optimize early diagnosis and surveillance of glaucoma as it allows timely treatment and improves patient outcomes.[114] Unless an early diagnosis and early treatment is offered to the patients, glaucoma patients may cause irreversible visual field (VF) loss. This is one of the clear clinical demands that could see the application of AI. Despite various constraints that have been experienced during AI research in glaucoma, including absence of multimodal evaluation and chronic natural progression, significant improvements have been achieved. Diagnosis of glaucoma with the help of structural changes many researchers have been able to make persistent use of AI through retinal fundus photos.[115]

AI IN SURGERY

The use of AI models in surgery is being adopted, although the quality research is a concern at present.[116] Applicability of AI has been extended even further and such areas as pre-operative complication prediction are considered which became prompt in terms of validation.[117] Interpretation of the images is yet another field that is growing in size, and the performance of the models in this respect is not consistent either, and most studies are not externally validated[118], Interest is evident in other spheres such as anatomy recognition[119] surgical decision making[120], and surgery-video analysis[121], clinical certification is an undermet precondition[122], and the issue of the lack of scientific rigor before deploying AI models as well as the problem of replication of results have become more prominent.[123] AI is nowadays applied in most other industrial fields, providing machines learning capacity through building data algorithms and developing an artificial neural network, internet-based learning, and computation. It used in health sector in being incorporated in to electronic health records, clinical algorithms and the interpretation of image data in pathology and radiology. Further, today, we can observe that AI is applied in the electrocardiogram study, interpretation of arterial blood gas, interpretation of certain radiological pictures like mammography, to a great number of medical areas.[124] Nowadays, many various industrial areas expose the application of AI and allow machines to learn integrating data algorithms and building artificial neural networks, internet-based learning, and computing skills. It is implemented in the health sector through being incorporated in the electronic medical records, clinical algorithms, and image data analysis in pathology, and radiology. Further, in the current world, we have witnessed that AI is being utilized in the computation of ECGs, the analysis of arterial blood gas, interpretation of certain radiographic images like mammography and so on in other areas also in the medical sector.[125] Robot is very common in surgery today but it is not completely combined with AI. It is a technologically advanced product ruled by sur-geons. High-quality image that meets 3-dimensional reality, improved freedom of movement with spring-loaded hand tools, the removal of any vibration during operations and the ability to be able to suture safely in tight spaces just as in open surgery are some of the benefits of RS. The smart tissue autonomous robot is the first example of robots that facilitate the work of the surgeon by using the AI technology and, even under the supervision of the surgeon, is capable of performing intestinal anastomoses with greater precision and even faster than the surgeons with significant experience.[126] In addition to the robots which aid the surgeon in doing his job, it is expected to achieve a device which simultaneously monitors every vital sign during the operation and utter verbal warnings when called, analyses all the current information required at any given moment, does pathological analyzing, and defines the surgical margins in solid organ tumors, applies his medical technique with zero error margin, and calculates about the postoperative complications, besides enlarging the vision and removing the hand trembling only.[127] Machine learning, computer vision, and robots have stimulated the exponential increase in AI applications in surgery, such as in this program by Jackson. Machine learning algorithms, which have the capability of analyzing massive files of data, are also being employed to build predictive models that will improve the outcomes in surgery. As an illustration, AI tools are able to suggest the likelihood of a successful surgery on the individual data of a patient to realize the best possible surgical plan. Also, computer vision solutions have become more advanced, and AI provides the opportunity to help identify and classify tissue in real-time during surgery which is vital in such operations as tumor removals.[128] Artificial intelligence has also been of great benefit in Robotic surgery. Contemporary robots have been developed with AI integrated into them to better target the surgeon s precision and accuracy of working, and have real time feedback and adjustments. All these systems have the ability of learning in every surgery conducted and becoming more and more precise and efficient. Repetitive activities, including suturing and tissue manipulation, can be accomplished by AI-powered robots rather unevenly, and surgeons can attend to the more complex parts of the operation.[129]

Although the utilisation of computer science in the operating room has already occurred (robotic assisted surgery), it is not linked to artificial intelligence. In fact, the current technology enhances the vision of the surgeon (3D cameras, near infra-red vision) and the mechanical feasibility (intuitive motion of the instruments, removal of tremor and scaling of movements), but cannot be translated into better patient outcome. Guidelines by the Society of American Gastrointestinal and Endoscopic Surgeons (SAGES) and the European Association for Endoscopic Surgery (EAES) on robotic assisted surgery[130], have not shown an improvement in patient outcome in comparing standard laparoscopic surgery procedures with robotic surgery assisted procedures. Therefore, a lot has been anticipated in virtue of upholding a better healthcare delivery once AI is integrated into the operating rooms. Artificial intelligence has lots of different forms in which it can be used in the OR: anesthesia support.[131] also surgical equipment monitoring. OR.NET[131], is a new project to combine the console of the operating room together in one shared interface to help devices communicate with each other to enhance the process of work and enhance patient safety.

The grandiose dream of the presence of AI during a real surgery is only at its early development stage. But the belief in learning by experience is not more than true in surgery. The more the surgeries that a person performs and the more diversity he finds, the greater the anatomical knowledge the surgeon possesses, thus he is able to operate inherently and more safely and faster. It is expected that the importance of introducing AI to the field of surgery will be reduced inaccuracy, enhanced safety, savings in the man power, the possibility to repeat the procedure along with the potential of some autonomous features. These misconceptions that stall the wheels of this direction, however, have logical basis that includes only the irrational aspect that it is a machine that will be controlling a human life and that mechanical complications in the operating room may lead to human death. The fact is that AI is already a part of our everyday lives and controls great numbers of human lives on daily basis in the form of mass transportation through automatic train operation in big cities, commercial aviation, and the latest development self-driving cars. Commercial flying is highly automated and auto pilots fly the planes with mere three to seven minutes of human control on the new Airbus and Boeing aircrafts.[132]

Table Application of AI in Healthcare.

Application Area	AI Tool / Technology	Example
Radiology	Deep Learning, CNNs	Detecting lung nodules in CT scans using AI-based image segmentation
Oncology	Machine Learning, Genomic AI	Predicting breast cancer treatment response using IBM Watson for Oncology
Cardiology	AI-enhanced ECG Analysis, CNNs	Identifying arrhythmias using AI interpretation of ECG signals
Gastroenterology	Computer Vision, CADe/CADx	Detecting colonic polyps during colonoscopy with real-time AI assistance
Ophthalmology	Deep Learning, Fundus Image AI	Screening for diabetic retinopathy using retinal image classification
Surgery	Computer Vision, Robotic AI	Smart Tissue Autonomous Robot (STAR) performing intestinal suturing
Drug Discovery	Generative AI, Predictive ML	Identifying new antibiotics using deep learning platforms
Medical Imaging	Neural Networks, Pattern Recognition	Detecting meningiomas in MRIs using automated segmentation tools
Pathology	NLP + Image Analysis	AI-assisted diagnosis from biopsy slides
Virtual Care	Chatbots, NLP,	Remote symptom triage via AI-powered

	Predictive Models	virtual assistants (e.g., Babylon Health)
Rehabilitation	Wearable AI, Motion Tracking	AI-based exoskeletons assisting in gait recovery post-stroke
Administrative Tasks	NLP, Automation	Automating medical coding and billing using AI-based EHR analysis
Pediatrics	Deep Learning, Risk Prediction	Predicting onset of sepsis in neonatal care using AI alert systems
Genomics	Predictive AI, Pattern Mining	Identifying cancer mutations through next-gen sequencing and AI modeling

Future Challenges of AI in Healthcare

However, AI in healthcare also has a series of challenges that are going to affect it in the future. Data privacy and security will still be a top priority since AI tools rely on large sets of sensitive data source.[133] There is also the issue of algorithmic bias as artificial intelligence may produce unfair results due to training data sets being uneven or biased in a certain direction.[134] Opaqueness of most AI models being commonly referred to as black boxes presents a threat to clinical confidence and decision.[21] To make the seamless use of AI in clinical workflows without overwhelming professionals, it is important to design AI and plan its use at the system level.[135] Besides, lack of effective regulatory framework to validate and govern liability comes in the way of adoption.[11] The majority of the models are based on the retrospective data inhibiting the possibility to apply them to the changing medical standards. Care providers should also have specific education to learn and utilize AI ethically.[8] Finally, a human new judgment should always be coupled with AI to care ethically and efficiently.[136]

CONCLUSION

The era of AI being predicted as a future trend is long gone, and it now is an innovation driver in healthcare. Ranging from the help of complex radiological interpretation to the improvement of early cancer detection and real-time surgical decision-making, AI has shown real value in various areas. Irrespective of these developments, the comprehensive introduction of AI into clinical use is limited to the regulatory barriers, data inconsistency, and professional admiration. To overcome such issues, one needs to not just fine tune the technology, but also have clear ethical protocols, training of clinicians and patient interaction. Better low-hanging fruit is to build human-AI cooperation in which machines complement clinical smarts and do not supplant them. Since research will still be under development, the role of AI in reaching more accurate, efficient and inclusive healthcare cannot be underestimated.

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