ISSN: 2993-5377

Review Article

Open Access Journal of Applied Science and Technology

Revolutionizing Medical Practice: The Impact of Artificial Intelligence (AI) on Healthcare

Shahin Javanmard*

Faculty of Medicine, Halic University, Türkiye

***Corresponding Author**
Shahin Javanmard, Faculty of Medicine, Halic University, Türkiye.

Submitted: 2023, Dec 13; **Accepted:** 2024, Jan 04; **Published:** 2024, Feb 19

Citation: Javanmard, S. (2024). Revolutionizing Medical Practice: The Impact of Artificial Intelligence (AI) on Healthcare. *OA J Applied Sci Technol, 2*(1), 01-16.

Abstract

The twenty-first century has witnessed significant advancements in informatics, reshaping our understanding of data processing and accessibility. Artificial intelligence (AI), encompassing techniques such as machine learning (ML), deep learning (DP), and neural networks (NN), is poised to revolutionize medicine. AI holds the capability of analyzing vast amounts of data, extracting meaningful insights, and making accurate predictions, thereby empowering industries to make informed decisions, drive innovation, and enhance efficiency. The landscape of medical AI has evolved significantly, demonstrating expert-level disease detection from medical images and promising breakthroughs across various industries. AI revolutionizes medical practice by leveraging advanced algorithms and machine learning capabilities to improve diagnostics, treatment planning, and overall patient care. However, the deployment of medical AI systems in regular clinical practice still needs to be tapped, presenting complex ethical, technical, and human-centered challenges that must be addressed for successful implementation. While AI algorithms have shown efficacy in retrospective medical investigations, their translation into practical medical settings has been limited, raising concerns about their usability and interaction with healthcare professionals. Moreover, the representativeness of retrospective datasets in real-world medical practice is subject to filtering and cleaning biases. Integrating AI into clinical medicine holds great promise for transforming healthcare delivery, improving patient care, and revolutionizing aspects such as diagnosis, treatment planning, drug discovery, personalized treatment, and medical imaging. With advanced algorithms and machine learning capabilities, AI and robotics in Healthcare can analyze large volumes of medical data, extract meaningful insights, and provide accurate predictions, empowering healthcare professionals to make informed decisions and optimize resource allocation. The availability of extensive clinical, genomics, and digital imaging data, coupled with investments from healthcare institutions and technology giants, underscores the potential of AI in healthcare. This review article explores AI's powerful potential to revolutionize healthcare delivery across multiple domains, emphasizing the need to overcome challenges and harness its transformative capabilities in clinical practice.

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DP), Neural Networks (NN), Drug Discovery Personalized Treatment, Medical Imaging, AI & Robotics in Healthcare

1. Introduction

As the century of technology progresses, the twenty-first century is distinguished by innovations in informatics that have fundamentally altered our understanding of data processing. Previously, the critical problem was acquiring access to information; however, in today's scientific community, fast-rising datasets are available at any time and can be quickly evaluated, shared, and kept in databases [1]. Innovations and New developments have increased human capabilities and hastened our scientific progress [2]. The phrase 'artificial intelligence'(AI), first used by John McCarthy in 1956, signifies the groundbreaking concept of simulating human intelligence in machines, revolutionizing various fields and paving the way for unprecedented technological advancements and problem-solving capabilities [3-5]. AI is set to revolutionize medicine in the coming years. The simulation of human intellect in computers is known as AI, and it includes techniques such as machine learning (ML), deep learning (DL), and neural networks (NN).

The landscape of medical AI has evolved significantly since the initial breakthroughs, where algorithms demonstrated expert-level disease detection from medical images. AI is rapidly developing and can change a wide range of industries. Because of the intriguing possibilities given by AI, the subject of medical physics, in particular, has experienced a boom in research. DL, aided by large amounts of data and fast computers, propels tremendous advances in algorithmic innovation and neural solid network models. Thanks to the availability of promising learning methods and abundant computer resources, AI is on the verge of changing medical physics research and practices. As a result, our community must be ready for future challenges and possibilities and take the lead in this new period of the fourth industrial revolution [6]. However, despite this progress, deploying medical AI systems in regular clinical practice remains an essential but primarily untapped prospect. Moreover, the medical AI community is currently grappling with complex ethical, technical, and human-centered challenges that must be overcome to ensure these systems' safe and successful translation [7]. While AI algorithms have repeatedly demonstrated efficacy in retrospective medical investigations, the translation of AI technologies into actual medical practice has been restricted [8]. Critics contend that AI systems may not be as helpful as retrospective data suggest since they are too sluggish or sophisticated for practical usage in real-world medical settings [9, 10]. Furthermore, difficulties may occur due to interactions between people and AI systems [11]. Again, retrospective in silico datasets are subjected to rigorous filtering and cleaning, which may reduce their representativeness in real-world medical practice [7]. As a fast-growing idea and technique, AI technology has found use in modern biology and biomedicine [12]. Its fundamental goal is to duplicate human-like intelligence on computers, allowing for the development of self-aware intelligent systems. AI's utilization includes vision, robotics, data analytics, problem-solving, Natural Language Processing, decision science, and linguistics [13, 14]. Similarly, AI technology has profoundly impacted clinical medicine, as evidenced by its growing influence on medical practice. Furthermore, AI-powered systems can assist in the early detection of diseases, facilitate personalized medicine approaches, and enhance the efficiency of administrative tasks. As AI advances, its integration into clinical medicine holds great promise for transforming healthcare delivery and improving overall patient care. Moreover, having the potential to revolutionize various aspects of healthcare delivery, including diagnosis, treatment planning, drug discovery, personalized treatment, and data analysis, AI is emerging as a powerful tool. With advanced algorithms and ML capabilities, AI can analyze large volumes of medical data, extract meaningful insights, and provide accurate predictions. This enables healthcare professionals to make more informed decisions, improve patient outcomes, and optimize resource allocation [15]. The required data is aided by clinical data from electronic health record (EHR) systems, genomics data from whole genome sequencing (WGS) studies, and digital imaging data from magnetic resonance (MR), ultrasound (US), biomedical research and digital pathology systems [15-20].

AI's capabilities are vast, drawing investment from premier hospitals such as the Mayo Clinic and the Cleveland Clinic and health-tech behemoths such as Philips, Siemens, and GE [4]. AI is used by biotech businesses such as BERG and pharmaceutical companies such as Takeda in biomarker identification and medication development [21, 22]. Google and Apple are other companies investing in AI-powered wearables that measure health and lifestyle [23]. Another example is The Preventive Health feature on Facebook, which connects people to health resources and checkup suggestions [24]. These trends represent the growth of American "Big Tech" or "GAFAM" corporations in healthcare, with AI revolutionizing the field. Multiple comprehensive evaluations have been published emphasizing AI's revolutionary influence on medicine and healthcare [4]. In this article, we discuss AI's powerful potential to revolutionize various aspects of healthcare delivery, including diagnosis and treatment planning, drug discovery, personalized treatment, and medical imaging.

2. Diagnosis and Treatment Planning

While the origins of clinical decision AI systems can be traced back to the 1970s, in recent years, DL has emerged as the predominant approach to enhance accurate and efficient diagnosis, aid in decision-making, reduce errors, streamline medical procedures, and enhance overall healthcare system effectiveness [25]. The significant advancement in medical diagnosis through image analysis is one of AI's remarkable achievements in medical practice. Early on, AI focused on diagnosing and treating diseases, exemplified by the development of MYCIN at Stanford in the 1970s for diagnosing blood-borne bacterial infections [26]. Although these early rule-based systems demonstrated promise in accurate diagnosis and treatment, they were not widely adopted in clinical practice [27]. They exhibited limited superiority over human diagnosticians and lacked seamless integration with healthcare workflows and medical record systems. As a result, initial enthusiasm waned when the challenges of training Watson to address specific cancer types and integrating them into care processes and systems became apparent [28, 29].

AI has revolutionized the field of diagnosis and treatment, offering valuable assistance and supplementary medical services. By leveraging language processing, automatic reasoning, and cognitive technology, AI-powered systems provide outstanding support in diagnosis and treatment. Integrating computer systems with intelligent-assisted diagnosis and treatment is akin to a machine brain, which incorporates vast medical knowledge and data analysis. This enables the system to simulate clinical thinking and diagnostic reasoning, combining patient histories and examination results to generate various diagnoses and corresponding treatment options. DL has been pivotal in advancing AI-assisted diagnosis and treatment technology, significantly improving access to medical attention. This has allowed patients to witness firsthand AI's crucial role in their daily lives [30]. Several AI solutions have moved from testing to actual application in recent years, gaining regulatory approval and overcoming administrative hurdles. For instance, the Centers for Medicare and Medicaid Services have played a critical role in supporting the use of specific AI systems in medical imaging diagnosis, easing their acceptance in clinical settings [31]. Furthermore, since 2020, the US Food and Drug Administration (FDA) has been increasingly approving AI products, particularly ML-based ones, but with lesser regulatory standards than complete approvals [32]. These FDA certifications have cleared the road for using AI and ML technologies in clinical practice. However, it is critical to recognize that the datasets utilized for these approvals frequently consist of private, unpublished retrospective data from a single institution. Therefore, enhanced reporting transparency and validation criteria must be established to build confidence in medical AI systems and demonstrate their influence on clinical outcomes [7].

DL, in which NN learns patterns directly from raw data, has gained significant success in picture categorization in recent years. As a result, medical AI research has exploded in fields that rely substantially on image interpretation, such as radiology, pathology, gastrointestinal, and ophthalmology. As an example, AI systems have made significant advances in radiology task accuracy, including mammography interpretation [33, 34], heart function assessment [35, 36], and lung cancer screening addressing not just a diagnosis but also risk prediction and therapy [37,38]. For instance, one AI system was taught to assess 3-year lung cancer risk based on radiologists' computed tomography (CT) readings and additional clinical data [39]. These forecasts might then be used to arrange follow-up CT scans for cancer patients, supplementing current screening regimens. Validation of such systems across many clinical locations and increasing prospective assessments have moved AI closer to deployment and practical effect in radiology [7]. AI has made significant advances in pathology, mainly through whole-slide imaging, in identifying tumors and delivering novel disease insights [40]. Models quickly recognized regions of interest within slides, possibly speeding up diagnostic operations. Aside from this practical impact, deep NN has been programmed to detect structural variations and driving mutations, delivering benefits beyond expert pathologist evaluations. Furthermore, AI has more accurately predicted survival for many cancer types than traditional grading and histological subtyping [41]. Research has shown how AI may improve pathology diagnoses' efficiency, accuracy, and utility [7].

DL has made significant progress in gastroenterology, specifically in enhancing colonoscopy, a crucial procedure for detecting colorectal cancer. By utilizing DL algorithms, it has been possible to accurately predict whether colonic lesions are cancerous, surpassing the performance of professional endoscopists [41]. Given that those polyps and other potential signs of cancer are often overlooked during colonoscopies, AI systems have been developed to assist endoscopists in their diagnosis [42]. These technologies have shown promising results in improving the ability of endoscopists to detect abnormalities, potentially increasing the sensitivity of colonoscopy and making it a more reliable diagnostic tool [7].

AI approaches for evaluating infectious illness data may be divided into two groups depending on their learning strategies: supervised learning and unsupervised learning. The process of inferring a function from labeled training data is supervised learning. Support Vector Machine (SVM), Decision Tree, Random Forest, Nave Bayes (NB), Artificial Neural Network (ANN), Bootstrap Aggregating, and AdaBoost are among the techniques included. These approaches rapidly handle classification and regression issues in medical data, enhancing diagnostic accuracy and recommending appropriate patient treatment choices [43, 44]. Furthermore, the predictions made by these methodologies may be used to inform authorities and the general public and provide recommendations for preventative and control tactics. Unsupervised learning methods, including Principal Component Analysis (PCA), can effectively reduce data dimensionality and assist in identifying critical features associated with infectious diseases [45]. Similarly, techniques like K-means enable grouping patients into subgroups and detecting unusual cases, allowing researchers to concentrate on these specific medical instances. Topic models such as Latent Dirichlet Allocation (LDA) can also extract relevant topics from textual medical records. The application of DL architectures has become prevalent in various domains, such as prediction and classification, social network filtering, and bioinformatics, providing valuable tools for analyzing infectious diseases [46]. The rapid progress in biological data, computational power, storage, and ML has propelled the integration of AI into the medical field. DL has emerged as a dominant approach, aiming to enhance diagnosis accuracy, support decision-making, minimize human errors, streamline medical procedures, and improve global health system efficiency [25]. Image analysis stands out as a remarkable and practical application of AI in medical practice, revolutionizing medical diagnosis [1]. Dermatology has also witnessed significant benefits from the integration of AI, as studies have consistently showcased AI's competence in accurately diagnosing and classifying various types of skin lesions. These studies have demonstrated a remarkable level of concordance between AI algorithms and expert dermatologists, underscoring the potential of AI to enhance dermatological practices. By leveraging AI's analytical capabilities and extensive datasets, dermatologists can potentially expedite the diagnosis process, improve treatment decision-making, and ultimately enhance patient outcomes [47].

In cardiology, the integration of ML and AI has accelerated interpretation and diagnosis processes. Electrocardiogram readings, echocardiography, SPECT imaging, cardiac CT angiography, and cardiac MRI have all benefited from AI automation, providing faster measurements and assessments of cardiac function [48]. Furthermore, including AI in electronic medical records (EMRs) has proven effective in detecting heart failure early and reducing mortality rates by identifying predictive patterns [49]. AI has also shown better predictive value than traditional methods in determining the appropriate interventional procedure for patients with angina, resulting in reduced mortality [50]. In gastroenterology, an AI-based system has been developed to improve the detection of abnormalities during endoscopic examinations. An illustrative example of such a case is Computer-Aided Detection and Diagnosis (CAD) systems, a type of computer system designed to assist in the detection and/or diagnosis of diseases, serving as a valuable "second opinion" for healthcare professionals. These systems aim to enhance the accuracy of radiologists while reducing interpretation time in image analysis. There are two primary categories of CAD systems: Computer-Aided Detection (CADe) systems and Computer-Aided Diagnosis (CADx) systems. CADe systems focus on locating lesions or abnormalities in medical images, while CADx systems specialize in characterizing these lesions, such as distinguishing between benign and malignant tumors. Using CAD systems in medical imaging is crucial in improving diagnostic precision and efficiency for healthcare professionals [51, 52]. In addition, the CADe system has demonstrated a high detection rate for colonic polyps and early gastric and colonic cancers, bridging the gap between experienced and less experienced endoscopists [53-55].

In ophthalmology, AI and DL have been proven effective in detecting diabetic retinopathy. In addition, studies have shown high sensitivity and specificity rates, indicating the potential for earlier diagnosis and improved management [56, 57]. However, further research is still needed in this field [58]. Nevertheless, AI has exhibited significant potential in these medical specialties, offering faster and more accurate diagnoses, improved treatment recommendations, and enhanced patient care [55].

AI also has shown great potential in the oncology field. AI applications have demonstrated promising breast cancer diagnosis and staging results, surpassing human readings. ML algorithms, such as Watson, have achieved high concordance rates with expert multidisciplinary tumor boards, providing reliable recommendations for breast cancer treatments [59]. In lung cancer detection, AI algorithms have exhibited superior accuracy to human experts, enabling accurate prognosis prediction and improved patient care [60]. In pathology analysis, AI algorithms have demonstrated outstanding diagnostic performance compared to pathologists, significantly reducing assessment time [61].

The application of AI in biomedicine has a critical focus on disease diagnosis. This field has made significant progress, enabling healthcare professionals to provide earlier and more accurate diagnoses for various diseases [62]. In vitro diagnostics utilizing biosensors or biochips are a vital component of primary diagnosis. AI plays a crucial role in interpreting gene expression data from microarrays, enabling the classification and detection of abnormalities [63, 64]. An emerging application is the classification of cancer microarray data to aid in cancer diagnosis [65]. Integrated AI systems, biosensors, and point-of-care testing (POCT) technology can potentially diagnose cardiovascular diseases at an early stage [66]. AI also has the capability to predict survival rates for cancer patients, including those with colon cancer [67]. While limitations of AI in biomedical diagnosis have been identified, researchers are actively working on mitigating these drawbacks [68]. Overall, AI holds immense potential in diagnostics and prognostics, paving the way for improved healthcare outcomes. Medical imaging and signal processing play a crucial role in disease diagnosis, management, and prediction. AI has been applied to extract features from biomedical signals, such as EEG, EMG, and ECG, enabling advancements in various fields like epileptic seizure prediction. DL has emerged as a reliable tool for seizure prediction, with the potential to be deployed on mobile systems. In biomedical image processing, AI has been utilized for image segmentation, multidimensional imaging, thermal imaging, and even portable ultrasonic devices in underserved regions. Additionally, AI can enhance standard decision support systems, improving diagnostic accuracy and disease management in areas like cancer, tropical diseases, and cardiovascular diseases. These applications highlight AI's power in early and accurate disease diagnosis, management, and prediction, as evidenced by case studies [2].

As AI advances, its potential for illness detection becomes clearer. With the incorporation of AI into regular clinical practice, we are on the verge of a new medical age. AI shows enormous promise in the field of gastrointestinal illness. It can improve endoscopic diagnostic skills, expedite workflow, and provide more accurate risk classification for gastrointestinal bleeding and neoplasia patients. However, additional study and validation of algorithms and their applications are required to realize AI's benefits fully. In addition, more clinical evidence is needed to establish AI's usefulness, value, and impact on patient care and outcomes. Furthermore, cost-effective AI models and solutions must be developed for healthcare practitioners and institutions to integrate AI into daily clinical operations. Somewhat perceiving AI as a rivalry between man and machine, clinicians should consider it a collaborative effort to improve therapeutic outcomes in gastrointestinal illnesses [25].

3. Drug Discovery

The pharmaceutical industry has long relied on computational methods for drug discovery, but the advent of AI has opened up new possibilities for enhancing the process [69]. This development has sparked enthusiasm within the scientific community and fostered collaborations between the pharmaceutical industry and AI companies [70]. A study revealed that the success rate of drug development for 21,143 compounds was only 5.2% in 2013, down from 11.2% in 2005, highlighting the need for AI to reduce attrition rates and costs [71]. Bringing a new drug to market typically takes 12 years and can incur expenses of up to 3 billion USD [72]. Additionally, with an overwhelming number of approximately 10^60 existing drug-like molecules, the task of discovering novel drugs is immense [73]. Current challenges in drug discovery include addressing drug toxicity, managing side effects, selecting suitable target sites, determining optimal dosages, and navigating intellectual property concerns [74]. It is common for the pharmaceutical industry to withhold pharmacokinetic and pharmacodynamic data until drugs receive approval [75].

In the current era of precision medicine, targeted drugs have become crucial for precise therapies. However, the process of bringing a new drug to market has traditionally been time-consuming and costly, averaging over one billion dollars in 10 years. Accelerating the drug discovery process and minimizing late-stage failures are pressing concerns for pharmaceutical companies in a highly competitive landscape. Additionally, historical data supports the broad deployment of AI and DL in this industry. Because of their transformational influence, AI and ML have become crucial in drug research and development. In particular, the integration of artificial NN and DL algorithms has transformed this field. For instance, peptide synthesis, structure-based virtual screening, ligand-based virtual screening, toxicity prediction, drug monitoring and release, pharmacophore modeling, quantitative structure-activity relationship analysis, drug repositioning, Poly pharmacology, and physiochemical activity evaluation have all been successful applications of ML and DL algorithms.

Chemical synthesis route prediction and process optimization are crucial in hastening new drug discovery and reducing production costs. Significant advancements have been made in AI-assisted drug discovery in recent years, benefiting both the discovery of new chemical entities and related business areas. The emergence of AI, encompassing ML, DL, expert systems, and artificial neural networks (ANNs), has revolutionized the field of drug discovery. AI is amp relationships and aspects of the discovery process, such as designing novel molecules, modeling protein and ligand structures, studying quantitative structure-activity relationships, and evaluating druggable properties. DL-based AI approaches have shown exceptional promise in addressing complex challenges encountered in drug discovery [76].

DL approaches offer significant advantages by integrating data at multiple levels through nonlinear models, surpassing the limitations of traditional AI and ML methods. This integration enables DL algorithms to deliver exceptional accuracy and precision while offering a more flexible architecture for problem-specific neural network design. Consequently, AI has found applications across various stages of drug discovery, encompassing target identification, hit discovery, lead optimization, ADMET prediction, and clinical trial design. Integrating AI into the drug discovery process holds great potential for driving innovation and efficiency in the pharmaceutical industry [75].

One of the first uses of AI/ML in early drug development was the measurement of "drug-likeness," which aims to replicate medicinal chemists' intuition in evaluating the possibility that novel chemical structures would become drugs. Even though drug (in the regulatory sense) is not an intrinsic property of chemicals", evaluating drug-likeness using AI/ML remains a useful chemical space navigation tool since the number of probable drug-like substances might surpass [77-79].

AI is revolutionizing the field of drug discovery by expediting the process and reducing reliance on time-consuming and costly physical experiments. DP models can predict crucial properties of potential drugs, such as bioactivity and toxicity, accelerating the identification of novel therapeutic compounds [80]. Remarkable successes have been achieved, including discovering a drug effective against antibiotic-resistant bacteria and targeting DDR1 in just a fraction of the time typically required [81]. These AI-designed molecules offer unique therapeutic avenues, contributing to the fight against drug-resistant pathogens. Furthermore, advancements in natural language processing, utilizing techniques like transformers and contextual word embeddings, have enabled the extraction of valuable insights from vast medical text datasets, empowering healthcare-related tasks [7].

Irrespective of the algorithms employed, these methods do not directly predict the attribute of a "drug." Instead, they assess multiparametric similarity, indicating that the molecules are similar to those considered of pharmaceutical interest by chemists. The lack of accurate harmful data has impeded a more rigorous approach due to drug-like fragments in over 40% of "non-drugs" as chemical vendors adapt their AI/ML drug-likeness models to increase sales to pharmaceutical companies [77]. However, recent advancements in AI/ML, mainly using Generative Adversarial Networks (GANs) combined with reinforcement learning (RL) and other architectures like variational auto-encoder, have provided encouraging outcomes and emerged as alternatives to conventional drug discovery tools [82]. GAN/RL methods have successfully generated molecules in silico based on desired chemical properties. Notably, significant progress has been made in molecular representation, including different encoding methods like chemical fingerprints, Simplified Molecular Input Line Systems (SMILES), and molecular graphs [83–86]. GAN techniques utilizing fingerprints, SMILES, chemical graphs, and 3D wave transforms have been proposed, each with distinct strengths regarding the amount and type of structural information retained or lost during encoding [83, 87, 88]. Another crucial aspect is molecular property profiles, where GAN architectures aim to generate chemically valid structures and molecules matching specific bioactivity, novelty, diversity profiles, and other desired features. Generative models have emerged to address these requirements, often combined with RL, resulting in various architectural designs. These approaches employ filters, reward functions, and evaluation metrics to ensure that the generated molecules possess suitable chemical properties, operating concurrently with the model architectures [79].

Despite the growing number of models, architectures, data types, and learning methods, assessing model performance remains challenging without a standardized benchmark and evaluation metrics referred to as a "gold standard." Platforms like Molecular Sets (MOSES) provide avenues to evaluate and compare the performance of generative models [89]. A significant milestone has been achieved in using generative chemistry for drug discovery, demonstrating that the generated molecules can be synthesized and exhibit activity in vitro, metabolic stability, and in vivo efficacy in disease-relevant models. Notably, the first example of an in vitro active molecule generated using the conditional adversarial autoencoder GAN was the JAK3 inhibitor [79].

Another generative model, Generative Tensorial Reinforcement Learning (GENTRL), was developed in vivo with active DDR1 and DDR2 inhibitors [81]. DDR1 and DDR2 inhibitors with varying characteristics and selectivity profiles were tested in vitro, followed by in vivo mice trials to confirm DDR1 antagonist pharmacokinetics.Due to the time and resources involved in each stage, the iterative process of design, manufacturing, testing, and evaluation in drug development is limited in the number of cycles it can support. Promising results from generative reinforcement learning technology in laboratory and animal studies indicate that AI/ML approaches are poised to become integral to the drug discovery cycle. However, validating molecules generated by generative and other ML systems takes significantly longer than building and training the models. While ongoing efforts globally exist to develop automated synthesis and in vitro validation systems, the synthesis and experimental validation processes will remain the primary factors determining the transformation of drug development through AI/ML in the coming years. Drug discovery poses significant challenges, including concerns about chemical structures such as toxicity, side effects, intellectual property, and selecting appropriate drug targets and optimal dosing for specific patient populations. Despite notable advancements in clinical pharmacology, the fragmented nature of late preclinical and clinical data remains a significant obstacle to effectively implementing AI/ML systems. Pharmaceutical companies typically withhold pharmacokinetic and pharmacodynamic data unless a medicine or combination of drugs is approved for human use.

In contrast to other research fields, only a tiny fraction of drug discovery data is accessible for developing AI/ML models, particularly for handling hazardous data. This limitation applies to distinguishing between "drugs" and "non-drugs" and AI/ML models targeting novel disease associations, understanding reasons for trial discontinuation or drug withdrawal, and accessing comprehensive datasets from successful clinical trials. Nevertheless, the current clinical development landscape is witnessing a significant transformation, and the adoption of AI/ML is growing [90].

In recent developments, Google's DeepMind has introduced AlphaFold, an AI tool trained on PDB structural data that accurately predicts the 3D structure of proteins from their amino acid sequences [75]. Similarly, Mohammed AlQuraishi from Harvard Medical School has designed a DL-based tool called Recurrent Geometric Network, which utilizes a single neural network to predict the 3D structure of proteins based on their amino acid sequences [91]. Quantum mechanics, although computationally demanding, can be made more user-friendly and effective with AI, as demonstrated by the development of SchNOrb. This DL-driven tool accurately predicts molecular orbitals and wave functions. AI also accelerates molecular dynamics (MD) simulations, as evidenced by the successful use of NN to predict free energies of transfer with similar accuracy to traditional MD simulations. De novo drug design has seen advancements with AI tools such as MolAIcal and ReLeaSE, which use DL algorithms for designing novel drugs.

Furthermore, AI has improved synthesis planning, retrosynthesis planning, and text mining-based drug discovery. AI technology has also proven valuable in primary and secondary drug screening, enhancing tasks such as cell classification and sorting, analyzing physical properties, and predicting toxicity. AI has great potential in optimizing the drug development process, addressing the challenges of identifying bioactive drug molecules and improving efficiency in various drug discovery and development stages [75].

The pharmaceutical industry faces significant challenges regarding time, cost, and coordination across various drug discovery and development stages. Identifying disease targets and formulating biological hypotheses can be time-consuming and expensive, often taking decades and costing billions of dollars. From identifying a hit molecule for a specific target to the final commercialization of a product, the average timeline is around 12.5 years. While clinical pharmacology data is expanding, it remains far less abundant compared to experimental chemistry and in vitro screening data. Limited studies with available data measure multiple parameters in vitro, animal models, and humans. Pharmaceutical companies consider this data a competitive advantage, making it challenging for AI/ML breakthroughs to disrupt clinical drug development. While integrating human intelligence and AI systems is expected in the coming decade, clinical pharmacologists will likely adapt slower than other drug discovery and development areas. However, clinical pharmacologists are strongly incentivized to embrace and monitor these advancements and understand the implications and risks associated with AI/ML systems in their daily practice. To accelerate AI/ML progress, there is a need for a collective effort from the community and regulatory bodies to promote open data sharing, particularly in the preclinical and clinical pharmacology domains. It is worth mentioning that the chemical generated by GENTRL resembles ponatinib, and guidelines for evaluating AI-generated compounds have been proposed by Walters and Murcko [90, 92].

In the pharmaceutical industry, AI has arisen as a potential answer to challenges caused by classical chemistry or chemical space, which impedes drug discovery and development. In addition, AI algorithms such as ML to DL have risen in computer-aided drug design (CADD) because of technical improvements and the development of advanced computers. AI has long been used by drug research and development scientists and chemists to anticipate chemical activity-structure connections. However, the emphasis is on improving drug discovery and development through ML algorithms that use classical chemistry concepts. The objective is to attain high accuracy and confidence scores, allowing chemists to use AI approaches to answer critical issues in medicinal chemistry. These questions involve deciding which chemical to explore next and comprehending the compound creation process [75]. Traditional chemistry-based drug development and computational drug design represent a potential future research direction. Collaborations involving systems biologists, chemical scientists, and computer specialists have created powerful ML methods and concepts that have revolutionized drug discovery and development. AI has the potential to solve traditional computer technique difficulties, such as time and computational costs, as well as dependability issues. Furthermore, ML-based methods have made it easier to determine the three-dimensional structure of a target protein, which is an essential step in drug development since it offers information about the ligand binding environment. AI and ML breakthroughs have considerably increased the relevance of computational approaches in drug development [93–96]. Furthermore, using unique data mining, curation, and management strategies has been critical in facilitating the creation of cutting-edge modeling algorithms. Advances in AI and DP provide a fantastic opportunity for rational medication design and discovery procedures, with the potential to tremendously influence humankind [75].

The pharmaceutical industry is grappling with rising costs and reduced efficiency in developing new drugs. However, the advent of ML and DL techniques supplies promising opportunities to address these challenges by enhancing cost-effectiveness, efficiency, and time savings in the drug discovery and development process. The recent advancements in AI algorithms, particularly in DL, coupled with improved hardware architecture and access to extensive datasets, signify the third wave of AI. This has sparked immense interest in applying AI approaches to drug development, leading to collaborations between pharmaceutical companies and AI firms, as well as the emergence of numerous startups in this field [97].

4. Personalized Medicine

Since traditional AI approaches involved the training algorithms on population data in identifying statistical patterns that aid in diagnosing and treating individuals based on their demographics and disease history, these approaches have successfully classified signals like electrocardiography for arrhythmia detection and analyzing radiology images for accurate diagnoses, leading AI to become a powerful tool for analyzing health data, finding applications in diagnostics, prognosis, and personalized care strategies. In addition, by uncovering impactful features, population-based AI approaches can illuminate the critical predictors of specific clinical outcomes, such as tacrolimus blood concentration.

The versatility of AI contributes to its widespread adoption in healthcare. However, the availability of high-quality training datasets that are representative, diverse, and sufficiently large can be limited for specific indications or patient scenarios. Unrepresentative datasets introduce biases, favoring specific symptoms or demographic groups and compromising the performance of AI in real-world scenarios with more complex disease manifestations. Additionally, cultural, ethnic, and gender biases in training datasets hinder the applicability of AI-derived knowledge to diverse subpopulations.

Collecting, annotating, and integrating medical data required for personalized medicine through population-based AI approaches is resource-intensive. In addition, more infrastructure is needed to apply AI-derived knowledge sustainably and equitably in treating individuals. Addressing these challenges is crucial for harnessing the full potential of AI in healthcare and ensuring its widespread and fair implementation [98].

AI might improve customized therapy by finding the most vulnerable persons based on individualized genetic and physiological traits [99]. Add to it the importance of AI in personalized medicine and genomes, epigenetics, transcriptomics, proteomics, metabolomics, and other multi-OMICS [99-103]. For instance, COVID-19 genomic research for analyzing the virus's eight subtypes are AI-backed procedures; these techniques lead to the development of novel diagnostics and therapies, which are also part of the output [104-106].

Personalized medicine is a revolutionary approach that tailors disease prognosis and medication based on an individual's genomics profile and health markers. It diverges from evidence-based medicine, which relies on average treatment effects for medication decisions. The goal of personalized medicine is to deliver the proper intervention at the right time and dose to the specific patient. It shifts the focus from reactive treatments, administered after symptoms appear, to pro-active treatments initiated at the preliminary stages of the disease, even before symptoms manifest.

Several factors have influenced the development of personalized medicine in the past decade. Advancements in gene sequencing technology, such as next-generation sequencing, have made genomics information more accessible and affordable. Initiatives like biobanks have emerged worldwide, pooling genomics data from hundreds of thousands of participants. The study of pharmacogenomics has gained momentum, highlighting the impact of one's genetic makeup on one's response to medication. Additionally, the availability of health record data, including MRI and CT scans, Electronic Medical Records (EMR), health claims, and mobile sensor data, enables the clustering of patient groups. AI, particularly ML, plays a crucial role in extracting valuable information from vast data. ML algorithms, including supervised and unsupervised learning, find correlations and patterns in the data. For instance, supervised learning predicts drug dosing effects for specific patient groups, while unsupervised learning and Deep Neural Networks (DNN) identify clusters and extract hidden patterns [107].

The use of AI in personalized medicine is a rapidly growing field with the potential to revolutionize healthcare. AI algorithms can analyze complex data from multiple sources, such as genomics, metabolomics, and clinical measures, to predict treatment outcomes and guide personalized therapy decisions [108].

Integrating AI algorithms with mechanistic modeling approaches has shown promise in increasing predictive performance and identifiability of parameters in personalized medicine. AI can serve as a predictive model for outcomes, integrate with mechanistic models for parameter optimization, and confirm mechanical models for accuracy. However, the successful implementation of personalized medicine requires standardized and representative data and collaboration between AI experts and disease specialists. AI findings must also be validated through more extensive clinical trials for translation into clinical practice [109].

AI-integrated computational modeling can improve the predictive performance of computational approaches in personalized medicine. Integrating statistical learning algorithms with mechanistic modeling approaches can enhance predictability and facilitate targeted intervention design [110].

A robust digital health technology platform, phenotypic personalized medicine (PPM), has been developed to address the challenge of optimizing drug doses for individual patients in combination therapy [98]. PPM utilizes patient-specific maps correlating drug inputs with phenotypic outputs, allowing personalized drug ratios and dosages.

Traditional approaches to multidrug optimization rely on drug pairing and lack dynamic optimization capabilities. In contrast, PPM is a powerful technology platform based on personalized medicine that continually adapts therapy based on patient response without requiring algorithms or predictive modeling. PPM optimizes drug dosages and identifies individualized synergism/antagonism by constructing personalized parabolic response maps for each patient. In a study focused on pediatric patients with standard-risk acute lymphoblastic leukemia (ALL), PPM was used to optimize combination chemotherapy doses, resulting in enhanced treatment outcomes and reduced chemotherapy amounts. PPM is a disease mechanism-independent approach that can be applied to various medical disciplines. The study examined the administration of four-drug maintenance therapy regimens in two patients with ALL. PPM optimization eliminated deviations in absolute neutrophil counts (ANC), and platelet counts outside target ranges by retrospectively optimizing drug ratios and dosages. The optimization process utilized patient clinical data and a robust parabolic correlation process, resulting in definitively optimized combination therapy administration.

PPM is not limited by the number of drugs that can be optimized and can provide patient-specific and dynamically optimized combination therapy regimens. It incorporates a curved response surface representing a patient's phenotypic response to drug treatment. The response surface can be continuously optimized throughout care, accounting for regimen changes and additional procedures. PPM implicitly considers disease biology, genetics, proteomics, and pharmacokinetics without requiring explicit knowledge of these elements.

The study demonstrated the potential of PPM in optimizing multidrug administration by conducting four-drug optimization assessments for the two patients. PPM optimization led to lower drug dosages for certain drugs compared to clinical dosing while maintaining treatment efficacy. Patient-specific drug response maps and quantitative drug interaction analysis provided insights into the factors contributing to treatment outcomes and facilitated personalized modulation of drug–dose ratios [111].

PPM represents a robust digital health technology platform applicable to various disorders. It enables continuous and dynamic optimization of combination therapy administration, improving response rates and reducing side effects. PPM overcomes the challenges of suboptimal dosing and combinatorial drug selection, allowing for rapid optimization and re-optimization throughout the drug development process. It can be utilized for population-wide administration as well as individualized combination therapy within a single patient.

Conventional approaches to personalizing patient regimens, such as dosing algorithms and pharmacogenomics, have limitations in dynamically optimizing care. PPM addresses these limitations by correlating patient response to therapy and providing continually optimized combination therapy regimens. It applies to various indications, including oncologic, infectious disease, cardiovascular, wound healing, and neurological conditions.

As an example, CURATE.AI is an AI-driven platform that is a PPM solution offering a unique personalized and customized treatment approach operating based on the observation that a quadratic polynomial equation can describe a varying input and measurable output in a complex system. CURATE.AI creates personalized individual profiles by mapping the relationship between intervention intensity and phenotypic results rather than complex drug interactions. It makes it both mechanism-independent and impactful on patients' lives. These profiles are a predictive tool to recommend the most effective intervention intensity. In addition, as patients' conditions change, the profiles dynamically recalibrate to ensure optimal treatment throughout the care. It selects the best combination therapy and dose for individuals based solely on their medical data, without requiring extensive population information. Furthermore, by utilizing NN and a quadratic surface relationship between dose and treatment efficacy, CURATE.AI optimizes phenotypic outcomes.

Beyond clinical settings, CURATE.AI has shown promise in treating cognitive profiles for personalized learning. By generating individualized profiles based on performance scores and training intensity, CURATE.AI recommends the optimal training strategies to maximize performance improvement, highlighting its potential in personalized learning and cognitive decline prevention [98].

Using clinical data, PPM-based optimization of combination therapy regimens can significantly improve patient outcomes. Prospective implementation of PPM has the potential to redefine treatment protocols and substantially enhance durable response rates by acquiring the correct data and perfecting therapy based on individual patient characteristics.

Implementing personalized medicine using AI algorithms faces challenges, including research and implementation costs, government regulations, and the need for changes in the medical profession and practice. Despite these challenges, AI-powered personalized medicine has the potential to save lives and improve the accuracy and precision of disease discovery, treatment, and drug administration.

Intelligent medical technologies, including AI-powered systems, enable a Predictive, Preventive, Personalized, and Participatory (4P) medicine model. These technologies empower patients and enable them to take an active role in their healthcare by providing access to personal health records, monitoring vital functions, and promoting optimal therapeutic compliance. In addition, augmented medicine, which combines AI-based technologies with other digital tools, such as surgical navigation systems and virtual reality tools, enhances various aspects of clinical practice. Nevertheless, the development of intelligent medical technologies, including AI-based systems, is transforming clinical practice and empowering patients in their healthcare journey [110].

Implementing AI in clinical practice is a promising and rapidly evolving field that aligns with precision medicine, genomics, and teleconsultation. While scientific progress in developing new healthcare solutions should remain rigorous and transparent, health policies must address the ethical and financial challenges of this transformative aspect of medicine [112]. Imaging, clinical, and genetic data have enabled AI techniques to predict grading, survival rates, and molecular genetics. They also have automated diagnosis, tissue segmentation for surgical planning, and post-treatment patient monitoring. While these techniques show promising performance, the application of AI to glioma diagnosis and treatment is still in its initial stages. Further development is necessary to assess the potential and implementation of these techniques in daily clinical practice and their impact on patient outcomes [109].

5. Medical Imaging

Over the past few decades, various medical imaging techniques, including CT, MRI, ultrasound, positron emission tomography (PET), mammography, and X-ray, have played a crucial role in early disease detection, diagnosis, and treatment [113,114]. Traditionally, human experts have been responsible for interpreting and analyzing medical images in clinical practice. However, a recent shift towards computer-aided diagnosis has benefited medical professionals. AI has significantly advanced, enabling machines to process and explain complex data [115]. Its application in the medical field, particularly in domains requiring imaging data analysis like radiology, ultrasound, pathology, dermatology, and ophthalmology, is extensive. AI, a profound learning algorithms, attracts significant attention due to its remarkable performance in image recognition tasks. These algorithms can automatically assess complex characteristics of medical images and enhance diagnostic accuracy with improved efficiency. AI is widely utilized and gaining popularity in medical imaging for liver diseases, including radiology, ultrasound, and nuclear medicine. By assisting physicians in reproductive imaging diagnoses, AI enhances accuracy and alleviates their workload [116].

Medical imaging informatics has been driving clinical research, translation, and practice for over three decades. This study highlights advancements in related research fields that promise to revolutionize imaging informatics in healthcare. These advancements aim to enable informed and more accurate diagnosis, timely prognosis, and effective treatment planning. Notably, many AI-based approaches that have obtained FDA approval focus on medical imaging informatics. The FDA serves as the official regulator of medical devices and, more recently, software-as-a-medical-device (SAMD). These solutions rely on machine or DP methodologies to perform various image analysis tasks, such as image enhancement, segmentation, detection of abnormalities, and estimation of malignancy likelihood. While FDA-approved applications primarily address radiology images, there are also some applications for digital pathology images [117].

The emergence of AI addresses the desire of healthcare professionals for improved efficacy and efficiency in clinical practice. AI can quantitatively assess imaging information automatically, eliminating reliance on qualitative reasoning [118]. Consequently, AI can assist physicians in making more accurate and reproducible imaging diagnoses, significantly reducing their workload. Two commonly used AI methods in medical imaging are traditional ML and DP algorithms [116].

Traditional ML algorithms rely on predefined engineered features, which describe regular patterns in data extracted from regions of interest (ROI) using explicit parameters based on expert knowledge. Computer programs mathematically define and quantify these task-specific features [119]. They can be further used to quantify various characteristics in medical imaging, such as lesion density, shape, and echo. Using these typical features, statistical ML models like support vector machines (SVM) or random forests are employed to identify relevant imaging-based biomarkers. Gatos et al [120]. attempted to utilize traditional ML algorithms to support liver fibrosis diagnosis through ultrasound images. However, predefined features often need more adaptability to accommodate changes in imaging modalities and associated signal-to-noise ratios.

On the other hand, DP algorithms, a subset of ML, are inspired by the neural network structure of the human brain. Unlike traditional algorithms, DP algorithms do not require the predefinition of features, or complex ROI placement on images [121, 122]. They can directly learn feature representations by exploring the data space and performing image classification and task processing. This data-driven approach enhances the informativeness and practicality of DP. Convolutional neural networks (CNNs) are currently the most popular DP architecture in medical image analysis [123]. CNNs often employ supervised learning through tagged data, while other architectures utilize unsupervised learning with untagged data. CNNs consist of multiple layers, with hidden layers responsible for feature extraction and aggregation through convolution and pooling operations. Fully connected layers perform high-level reasoning before producing the final output. Several studies have demonstrated the exceptional performance of DP methods in staging tasks in computed tomography (CT), segmentation tasks in MRI, and detection tasks in ultrasound [116].

Despite notable advancements in AI application in medical imaging and significant investments in supporting technology and companies, radiologists need to be faster to adopt AI in their practice. Only 56% of radiologists currently use some form of AI, and exposure to common AI use cases, such as image tagging for critical patients, workflow optimization, automated image analysis, decision support for clinicians, and imaging quality enhancement, ranges from 22% to 38%. Moreover, only 10% of radiologists consider themselves "very familiar" with these applications. The primary barrier hindering AI adoption in medical imaging is the radiologists themselves, as 40% of survey respondents stated. Interestingly, this resistance does not stem from a fear of AI replacing their traditional roles, as only 16% expressed this concern. Instead, many radiologists exhibit skepticism regarding the current diagnostic capabilities of AI, especially for complex patients or disease states. The second significant barrier is the lack of regulatory approval, cited by 32% of respondents. However, this may change as more algorithms receive support or if the FDA updates its regulatory framework to accommodate modifications to AI- and ML-based software as medical devices. Recognizing the transformative potential of AI and ML, the FDA published a discussion paper in April 2019 outlining a potential approach to premarket review for such software modifications [124]. This proposed approach aims to ensure patient safety, implement specified change protocols, and continuously monitor algorithm performance throughout the product lifecycle.

While these proposed changes would clarify the approval process and facilitate safe and effective algorithm updates, it is crucial for AI and ML startups, as well as established players, to stay informed about updates to the regulatory framework and provide input to the FDA as appropriate. Despite the current regulatory framework, there has been an acceleration in FDA approvals for AI and ML algorithms. The FDA has approved at least 16 AI-based applications, with the pace of approvals significantly increasing since 2018. The first approval was granted in late 2016 to RiverRain Technologies for an application assisting in detecting lung nodules in CT scans, followed by additional support in 2017.

The potential impact of AI on the medical imaging market and radiologists' work is significant. It has the potential to enhance scan speed, improve diagnostic accuracy, and alleviate the workload of radiologists, ultimately leading to better patient outcomes. The pace at which this market develops relies partly on addressing the skepticism some radiologists have regarding AI's capabilities. Additionally, obtaining FDA approval and securing reimbursement from payers are significant hurdles that AI companies must navigate. Nevertheless, given the increasing evidence of AI's effectiveness in medical imaging, it is challenging to envision a future where AI only partially revolutionizes the field of radiology [125].

DP employs DNNs to tackle various tasks. These networks are designed to learn and extract abstract representations at distinct levels, allowing them to grasp complex functions. In the case of image inputs, the lower-level features typically capture edges and contours, while higher-level features encompass semantic characteristics. An essential advantage of DP is its ability to automatically learn and optimize feature extraction parameters using the available data samples. This eliminates the need for manual feature engineering, resulting in improved performance tailored to specific problems [114].

DP has profoundly affected medical imaging, revolutionizing the field and significantly improving diagnostic accuracy and patient care. Unlike traditional ML approaches, DP models are powerful and complex networks comprising artificial neurons that can automatically learn essential features from vast amounts of data. This capability enables them to extract valuable information, facilitate disease diagnosis, and even offer prognoses in the healthcare domain. With the advent of CNNs and other DP techniques, medical images can be analyzed with exceptional precision and speed. DP models can learn intricate patterns and features within images, enabling them to detect abnormalities, identify specific diseases, and assist in treatment planning. The ability of DP algorithms to automatically extract relevant information from medical images has led to enhanced early detection, more accurate diagnoses, and personalized treatment options. As medical data increasingly transition to digital formats, the potential of DP models in all facets of medicine is expanding exponentially [126, 127].

Moreover, DP algorithms continue to evolve and improve as they learn from larger datasets, contributing to advancements in medical imaging technology. Patients will soon have the opportunity to engage with AI-based medical systems, providing them with safe and convenient healthcare experiences. These intelligent systems promise to enhance patient care and well-being genuinely, empowering healthcare professionals with powerful tools to make informed decisions and improve patient outcomes [127].

In recent years, significant advancements have been made in deep-learning techniques using convolutional networks (ConvNets). Kermany et al. demonstrated that transfer learning involves leveraging pre-trained ConvNets on publicly available datasets to build an AI system. This approach enables the transfer of knowledge gained from training ConvNets to recognize animals in images to detect retinal diseases in optical coherence tomography (OCT) images. Kermany et al. have shown impressive deep-learning diagnostic performance in detecting retinal conditions and pediatric pneumonia using OCT and chest X-ray (CXR) images, respectively. They also highlighted the value of transfer learning in situations with limited datasets. However, despite these advancements, DP for medical imaging analysis still needs to answer many questions. Collaboration between the ML and medical communities is crucial to developing and validating DP techniques and strategically deploying them in patient care.

ConvNets consist of multiple layers of trainable neurons that can learn features and patterns. Inspired by the visual cortex in the brain, each neuron in a ConvNet is connected to a local region of inputs to learn specific image features. Various publicly available ConvNet models, such as VGGNet, have been successfully utilized in medical imaging. Kermany et al. demonstrated the promising diagnostic applications of DP and transfer learning in detecting primary retinal conditions using OCT images. The authors evaluated the AI performance using three models—multiclass comparison, limited model, and binary classifiers. DP achieved over 90% accuracy in differentiating retinal conditions and standard images, with the binary classifiers model achieving the highest accuracy of over 98%. Despite a slight drop in accuracy, even the limited model achieved over 90% accuracy despite being trained on a significantly smaller dataset. The DP system showed similar outcomes to human experts in identifying individuals requiring urgent referral based on OCT images. Before implementing this approach in clinical settings, several considerations should be addressed. Direct comparisons with existing DP systems are necessary to assess relative merits, limitations, performance, efficiency, and ease of use.

Furthermore, the approach's applicability to other diseases or imaging modalities should be carefully evaluated. It is crucial to determine the optimal application scenarios, whether screening the general population in primary healthcare or aiding ophthalmologists in tertiary care settings. Future studies should address challenges in medical imaging, such as differences between machine and human adjudication and methods to assess and explain sources of error quantitatively and qualitatively [128].

AI's potential in diagnostic medical imaging is being extensively evaluated, showing impressive accuracy and sensitivity in detecting imaging abnormalities and offering improved tissue-based detection and characterization. However, heightened sensitivity brings a crucial challenge: identifying subtle changes with uncertain clinical significance. For instance, a study analyzing screening mammograms revealed that artificial NN is equally accurate to radiologists in cancer detection but consistently exhibits higher sensitivity for pathological findings, particularly subtle lesions. As we embark on an AI-assisted revolution in diagnostic imaging, the medical community must anticipate the unknowns associated with this technology and ensure its effective and safe integration into clinical practice. Evaluating AI's potential risks and benefits in light of its unique capabilities is pivotal to establishing its role in clinical medicine. Striking a balance between enhanced detection and overdiagnosis poses a significant challenge. Key to this assessment is the consistent use of out-of-sample external validation and well-defined cohorts, enhancing the quality and interpretability of AI studies. While many AI imaging studies focus on estimating diagnostic accuracy through sensitivity and specificity calculations, clinically relevant outcomes should be considered. Relevant outcome variables include new diagnoses of advanced diseases, diseases requiring treatment, or conditions likely to impact long-term survival, as they strongly affect the quality of life. While numerous studies demonstrate higher specificity and lower recall rates of AI than standard reading, they often overlook lesion type and biological aggressiveness when assessing accuracy and sensitivity. Non-patient-centric endpoint selection may increase sensitivity but at the cost of higher false positives and potentially over-diagnosing minor changes that could represent subclinical or indolent diseases. A significant challenge lies in AI's ability to identify imaging pattern changes that are not easily discernible to humans, unlike discrete findings from traditional radiographic studies. For instance, ML analysis of brain MRI can recognize tissue changes suggestive of early ischemic stroke with greater sensitivity than human readers within a narrow time window from symptom onset. However, the correlation between subtle parenchymal brain alterations identified by AI and neurological outcomes, such as functional disability or responsiveness to thrombolysis, remains unknown and necessitates dedicated studies.

Furthermore, complex situations may arise when AI recommends treatment without a well-defined abnormality detected on routine imaging. Such discrepancies confuse and potentially erode trust, highlighting the need for public education on the concept of DP in imaging analysis. Additionally, medical liability concerns, such as failure to diagnose or potentially unnecessary surgeries, may arise if AI becomes the standard of care. It is vital to reassure the public, especially physicians, that AI is unlikely to replace radiologists entirely but will enhance their productivity when utilized alongside AI [129].

6. Conclusion

AI's impact on healthcare can revolutionize medical practice and improve patient care. The rapid development of AI, encompassing ML, DP, and NN techniques, has enabled significant advancements in various industries, including medicine. The field of medical physics, in particular, has experienced a surge in research driven by AI's promising learning methods and the availability of abundant computer resources. However, despite progress, deploying AI systems in regular clinical practice remains an untapped prospect. The medical AI community faces complex challenges in ethics, technical feasibility, and human-centered interactions that need to be overcome for the safe and successful translation of these systems. Critics argue that the effectiveness of AI systems in real-world medical settings may not be as significant as retrospective data suggests, raising concerns about their practical usability and potential limitations.

Nevertheless, AI technology has already made a profound impact on clinical medicine. Its applications, from disease detection and personalized medicine to administrative efficiency, have demonstrated promising results. AI-powered systems can assist in early disease detection, facilitate personalized treatment approaches, optimize resource allocation, enable healthcare professionals to make more informed decisions, and improve patient outcomes.

Integrating AI into clinical medicine holds tremendous promise for transforming healthcare delivery. With advanced algorithms and ML capabilities, AI can analyze vast medical data, extract valuable insights, and provide accurate predictions. This empowers healthcare professionals to deliver superior care, improve diagnosis and treatment planning, streamline drug discovery processes, and enhance overall data analysis in biomedicine.

Thanks to AI technology, the remarkable breakthroughs witnessed in biomedicine have been made possible by the availability of extensive clinical data, genomics data, and digital imaging data. Leading hospitals, biotech companies, and health tech giants have recognized the immense potential of AI in healthcare and have made substantial investments in its development and application.

In conclusion, AI has emerged as a powerful tool that has the potential to revolutionize various aspects of healthcare delivery. As AI advances, the medical community must address the challenges and embrace the opportunities it presents. By leveraging the capabilities of AI and harnessing its potential, healthcare professionals can drive healthcare transformation, resulting in improved patient care, enhanced diagnostics, personalized treatments, and more efficient data analysis in the years ahead.

References

1. Athanasopoulou, K., Daneva, G. N., Adamopoulos, P. G., & Scorilas, A. (2022). Artificial intelligence: the milestone in modern biomedical research. *BioMedInformatics, 2*(4), 727-744.
2. Rong, G., Mendez, A., Assi, E. B., Zhao, B., & Sawan, M. (2020). Artificial intelligence in healthcare: review and prediction case studies. *Engineering,* 6(3), 291-301.
3. Keskinbora, K. H. (2019). Medical ethics considerations on artificial intelligence. *Journal of clinical neuroscience, 64*, 277-282.
4. Hulsen, T. (2022). Literature analysis of artificial intelligence in biomedicine. *Annals of translational medicine, 10*(23).
5. Solomonoff, R. J. (1985). The time scale of artificial intelligence: Reflections on social effects. *Human Systems Management, 5*(2), 149-153.
6. Xing, L., Krupinski, E. A., & Cai, J. (2018). Artificial intelligence will soon change the landscape of medical physics research and practice. *Medical physics, 45*(5), 1791-1793.
7. Rajpurkar, P., Chen, E., Banerjee, O., & Topol, E. J. (2022). AI in health and medicine. *Nature medicine, 28*(1), 31-38.
8. Wiens, J., Saria, S., Sendak, M., Ghassemi, M., Liu, V. X., Doshi-Velez, F., ... & Goldenberg, A. (2019). Do no harm: a roadmap for responsible machine learning for health care. *Nature medicine, 25*(9), 1337-1340.
9. Kanagasingam, Y., Xiao, D., Vignarajan, J., Preetham, A., Tay-Kearney, M. L., & Mehrotra, A. (2018). Evaluation of artificial intelligence–based grading of diabetic retinopathy in primary care. *JAMA network open, 1*(5), e182665-e182665.
10. Beede, E., Baylor, E., Hersch, F., Iurchenko, A., Wilcox, L., Ruamviboonsuk, P., & Vardoulakis, L. M. (2020, April). A human-centered evaluation of a deep learning system deployed in clinics for the detection of diabetic retinopathy. In *Proceedings of the 2020 CHI conference on human factors in computing systems* (pp. 1-12).
11. Kiani, A., Uyumazturk, B., Rajpurkar, P., Wang, A., Gao, R., Jones, E., ... & Shen, J. (2020). Impact of a deep learning assistant on the histopathologic classification of liver cancer. *NPJ digital medicine,* 3(1), 23.
12. Leite, M. L., de Loiola Costa, L. S., Cunha, V. A., Kreniski, V., de Oliveira Braga Filho, M., da Cunha, N. B., & Costa, F. F. (2021). Artificial intelligence and the future of life sciences. *Drug Discovery Today, 26*(11), 2515-2526.
13. Hamet, P., & Tremblay, J. (2017). Artificial intelligence in medicine. *Metabolism, 69,* S36-S40.
14. Bhardwaj, A., Kishore, S., & Pandey, D. K. (2022). Artificial intelligence in biological sciences. *Life, 12*(9), 1430.
15. Hulsen, T., Jamuar, S. S., Moody, A. R., Karnes, J. H., Varga, O., Hedensted, S., ... & McKinney, E. F. (2019). From big data to precision medicine. *Frontiers in medicine, 6*, 34.
16. Ross, M. K., Wei, W., & Ohno-Machado, L. (2014). "Big data" and the electronic health record. *Yearbook of medical informatics, 23*(01), 97-104.
17. Suwinski, P., Ong, C., Ling, M. H., Poh, Y. M., Khan, A. M., & Ong, H. S. (2019). Advancing personalized medicine through the application of whole exome sequencing and big data analytics. *Frontiers in genetics, 10*, 49.
18. Tahmassebi, A., Gandomi, A. H., McCann, I., Schulte, M. H., Goudriaan, A. E., & Meyer-Baese, A. (2018). Deep learning in medical imaging: fmri big data analysis via convolutional neural networks. In *Proceedings of the practice and experience on advanced research computing* (pp. 1-4).
19. Van Sloun, R. J., Cohen, R., & Eldar, Y. C. (2019). Deep learning in ultrasound imaging. *Proceedings of the IEEE, 108*(1), 11-29.
20. Madabhushi, A., & Lee, G. (2016). Image analysis and machine learning in digital pathology: Challenges and opportunities. *Medical image analysis, 33,* 170-175.
21. Tolstikov, V., Moser, A. J., Sarangarajan, R., Narain, N. R., & Kiebish, M. A. (2020). Current status of metabolomic biomarker discovery: impact of study design and demographic characteristics. *Metabolites, 10*(6), 224.
22. Savage, N. (2020). The race to the top among the world's leaders in artificial intelligence. *Nature, 588*(7837), S102-S102.
23. Sutner S. Google, Fitbit. (2021). startups storm into healthcare AI. 2021.
24. Facebook. Preventive Health. 2021.
25. Kaul, V., Enslin, S., & Gross, S. A. (2020). History of artificial intelligence in medicine. *Gastrointestinal endoscopy, 92*(4), 807-812.
26. Savage, N. (2022). Breaking into the black box of artificial intelligence. *Nature*.
27. Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future healthcare journal, 6*(2), 94.
28. Chen, C., Wu, T., Guo, Z., & Cheng, J. (2021). Combination of deep neural network with attention mechanism enhances the explainability of protein contact prediction. *Proteins: Structure, Function, and Bioinformatics, 89*(6), 697-707.
29. Canzoneri, R., Lacunza, E., & Abba, M. C. (2019). Genomics and bioinformatics as pillars of precision medicine in oncology.
30. Feng, Z. H. A. O., & Hua, X. U. (2022, June). Applications and Current Status of AI in the Medical Field. In *Journal of Physics: Conference Series* (Vol. 2289, No. 1, p. 012030). IOP Publishing.
31. "Centers for Medicare & Medicaid Services. Medicare Program; Hospital Inpatient Prospective Payment Systems for Acute Care Hospitals and the Long-Term Care Hospital Prospective Payment System and Final Policy Changes and Fiscal Year 2021 Rates; Quality Reporting and Medicare and Medicaid Promoting Interoperability Programs Requirements for Eligible Hospitals and Critical Access Hospitals. Fed. Regist. 85, 58432–59107 (2020)."
32. Benjamens, S., Dhunnoo, P., & Meskó, B. (2020). The state of artificial intelligence-based FDA-approved medical devices and algorithms: an online database. *NPJ digital medicine, 3*(1), 118.
33. Wu, N., Phang, J., Park, J., Shen, Y., Huang, Z., Zorin, M., ... & Geras, K. J. (2019). Deep neural networks improve radiologists' performance in breast cancer screening. *IEEE transactions on medical imaging, 39*(4), 1184-1194.

34. McKinney, S. M., Sieniek, M., Godbole, V., Godwin, J., Antropova, N., Ashrafian, H., ... & Shetty, S. (2020). International evaluation of an AI system for breast cancer screening. *Nature, 577*(7788), 89-94.
35. Ghorbani, A., Ouyang, D., Abid, A., He, B., Chen, J. H., Harrington, R. A., ... & Zou, J. Y. (2020). Deep learning interpretation of echocardiograms. *NPJ digital medicine, 3*(1), 10.
36. Ouyang, D., He, B., Ghorbani, A., Yuan, N., Ebinger, J., Langlotz, C. P., ... & Zou, J. Y. (2020). Video-based AI for beat-to-beat assessment of cardiac function. *Nature, 580*(7802), 252-256.
37. Ardila, D., Kiraly, A. P., Bharadwaj, S., Choi, B., Reicher, J. J., Peng, L., ... & Shetty, S. (2019). End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography. *Nature medicine, 25*(6), 954-961.
38. Huynh, E., Hosny, A., Guthier, C., Bitterman, D. S., Petit, S. F., Haas-Kogan, D. A., ... & Mak, R. H. (2020). Artificial intelligence in radiation oncology. *Nature Reviews Clinical Oncology, 17*(12), 771-781.
39. Huang, W., Harnagea, C., Tong, X., Benetti, D., Sun, S., Chaker, M., ... & Nechache, R. (2019). Epitaxial Bi2FeCrO6 multiferroic thin-film photoanodes with ultrathin p-type NiO layers for improved solar water oxidation. *ACS applied materials & interfaces, 11*(14), 13185-13193.
40. Kather, J. N., Pearson, A. T., Halama, N., Jäger, D., Krause, J., Loosen, S. H., ... & Luedde, T. (2019). Deep learning can predict microsatellite instability directly from histology in gastrointestinal cancer. *Nature medicine, 25*(7), 1054-1056.
41. Zhou, D., Tian, F., Tian, X., Sun, L., Huang, X., Zhao, F., ... & Li, X. (2020). Diagnostic evaluation of a deep learning model for optical diagnosis of colorectal cancer. *Nature communications, 11*(1), 2961.
42. Zhao, S., Wang, S., Pan, P., Xia, T., Chang, X., Yang, X., ... & Bai, Y. (2019). Magnitude, risk factors, and factors associated with adenoma miss rate of tandem colonoscopy: a systematic review and meta-analysis. *Gastroenterology, 156*(6), 1661-1674.
43. Foster, K. R., Koprowski, R., & Skufca, J. D. (2014). Machine learning, medical diagnosis, and biomedical engineering research-commentary. *Biomedical engineering online, 13,* 1-9.
44. Kononenko, I. (2001). Machine learning for medical diagnosis: history, state of the art and perspective. *Artificial Intelligence in medicine, 23*(1), 89-109.
45. Wang, Y., Fan, Y., Bhatt, P., & Davatzikos, C. (2010). High-dimensional pattern regression using machine learning: from medical images to continuous clinical variables. *Neuroimage, 50(*4), 1519-1535.
46. Wong, Z. S. Y., Bui, C. M., Chughtai, A. A., & Macintyre, C. R. (2017). A systematic review of early modelling studies of Ebola virus disease in West Africa. *Epidemiology & Infection, 145*(6), 1069-1094.
47. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *nature, 542*(7639), 115-118.
48. Slomka, P. J., Dey, D., Sitek, A., Motwani, M., Berman, D. S., & Germano, G. (2017). Cardiac imaging: working towards fully-automated machine analysis & interpretation. *Expert review of medical devices, 14*(3), 197-212.
49. Choi, E., Schuetz, A., Stewart, W. F., & Sun, J. (2017). Using recurrent neural network models for early detection of heart failure onset. *Journal of the American Medical Informatics Association, 24*(2), 361-370.
50. Buzaev, I. V., Plechev, V. V., Nikolaeva, I. E., & Galimova, R. M. (2016). Artificial intelligence: Neural network model as the multidisciplinary team member in clinical decision support to avoid medical mistakes. *Chronic diseases and translational medicine, 2*(03), 166-172.
51. Karkanis, S., Magoulas, G. D., & Theofanous, N. (2000). Image recognition and neuronal networks: Intelligent systems for the improvement of imaging information. *Minimally Invasive Therapy & Allied Technologies, 9*(3-4), 225-230.
52. Firmino, M., Angelo, G., Morais, H., Dantas, M. R., & Valentim, R. (2016). Computer-aided detection (CADe) and diagnosis (CADx) system for lung cancer with likelihood of malignancy. *Biomedical engineering online, 15*(1), 1-17.
53. Misawa, M., Kudo, S. E., Mori, Y., Cho, T., Kataoka, S., Yamauchi, A., ... & Mori, K. (2018). Artificial intelligence-assisted polyp detection for colonoscopy: initial experience. *Gastroenterology, 154*(8), 2027-2029.
54. Kanesaka, T., Lee, T. C., Uedo, N., Lin, K. P., Chen, H. Z., Lee, J. Y., ... & Chang, H. T. (2018). Computer-aided diagnosis for identifying and delineating early gastric cancers in magnifying narrow-band imaging. *Gastrointestinal endoscopy, 87*(5), 1339-1344.
55. Mintz, Y., & Brodie, R. (2019). Introduction to artificial intelligence in medicine. *Minimally Invasive Therapy & Allied Technologies, 28*(2), 73-81.
56. Organization WH. (2016). Global Report on Diabetes.
57. Yau, J. W., Rogers, S. L., Kawasaki, R., Lamoureux, E. L., Kowalski, J. W., Bek, T., ... & Meta-Analysis for Eye Disease (META-EYE) Study Group. (2012). Global prevalence and major risk factors of diabetic retinopathy. *Diabetes care, 35*(3), 556-564.
58. Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., ... & Webster, D. R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *jama, 316*(22), 2402-2410.
59. Korbar, B., Olofson, A. M., Miraflor, A. P., Nicka, C. M., Suriawinata, M. A., Torresani, L., ... & Hassanpour, S. (2017). Deep learning for classification of colorectal polyps on whole-slide images. *Journal of pathology informatics, 8*(1), 30.
60. Yu, K. H., Zhang, C., Berry, G. J., Altman, R. B., Ré, C., Rubin, D. L., & Snyder, M. (2016). Predicting non-small cell lung cancer prognosis by fully automated microscopic pathology image features. *Nature communications, 7*(1), 12474.
61. Bejnordi, B. E., Veta, M., Van Diest, P. J., Van Ginneken, B., Karssemeijer, N., Litjens, G., ... & CAMELYON16 Consortium. (2017). Diagnostic assessment of deep

learning algorithms for detection of lymph node metastases in women with breast cancer. *Jama, 318*(22), 2199-2210.
62. Sajda, P. (2006). Machine learning for detection and diagnosis of disease. Annu. *Rev. Biomed. Eng., 8,* 537-565.
63. Molla, M., Waddell, M., Page, D., & Shavlik, J. (2004). Using machine learning to design and interpret gene-expression microarrays. *AI Magazine, 25*(1), 23-23.
64. Grant, G. R., Manduchi, E., & Stoeckert Jr, C. J. (2007). Analysis and management of microarray gene expression data. *Current protocols in molecular biology, 77*(1), 19-6.
65. W Shi, T., S Kah, W., S Mohamad, M., Moorthy, K., Deris, S., F Sjaugi, M., ... & Kasim, S. (2017). A review of gene selection tools in classifying cancer microarray data. *Current Bioinformatics, 12*(3), 202-212.
66. Vashistha, R., Dangi, A. K., Kumar, A., Chhabra, D., & Shukla, P. (2018). Futuristic biosensors for cardiac health care: an artificial intelligence approach. *3 Biotech, 8,* 1-11.
67. Ahmed, F. E. (2005). Artificial neural networks for diagnosis and survival prediction in colon cancer. *Molecular cancer, 4*(1), 1-12.
68. Foster, K. R., Koprowski, R., & Skufca, J. D. (2014). Machine learning, medical diagnosis, and biomedical engineering research-commentary. Biomedical engineering online, 13, 1-9.
69. Jiménez-Luna, J., Grisoni, F., & Schneider, G. (2020). Drug discovery with explainable artificial intelligence. *Nature Machine Intelligence, 2*(10), 573-584.
70. Cavasotto, C. N., & Di Filippo, J. I. (2021). Artificial intelligence in the early stages of drug discovery. *Archives of biochemistry and biophysics, 698*, 108730.
71. Wong, C. H., Siah, K. W., & Lo, A. W. (2019). Estimation of clinical trial success rates and related parameters. *Biostatistics, 20*(2), 273-286.
72. DiMasi, J. A., Grabowski, H. G., & Hansen, R. W. (2016). Innovation in the pharmaceutical industry: new estimates of R&D costs. *Journal of health economics, 47*, 20-33.
73. Ruddigkeit, L., Van Deursen, R., Blum, L. C., & Reymond, J. L. (2012). Enumeration of 166 billion organic small molecules in the chemical universe database GDB-17. *Journal of chemical information and modeling, 52*(11), 2864-2875.
74. Mohs, R. C., & Greig, N. H. (2017). Drug discovery and development: Role of basic biological research. *Alzheimer's & Dementia: Translational Research & Clinical Interventions, 3*(4), 651-657.
75. Gupta, R., Srivastava, D., Sahu, M., Tiwari, S., Ambasta, R. K., & Kumar, P. (2021). Artificial intelligence to deep learning: machine intelligence approach for drug discovery. *Molecular diversity, 25*, 1315-1360.
76. Xu, Y., Liu, X., Cao, X., Huang, C., Liu, E., Qian, S., ... & Zhang, J. (2021). Artificial intelligence: A powerful paradigm for scientific research. *The Innovation, 2*(4).
77. Ursu, O., & Oprea, T. I. (2010). Model-free drug-likeness from fragments. *Journal of chemical information and modeling, 50*(8), 1387-1394.
78. Gayvert, K. M., Madhukar, N. S., & Elemento, O. (2016). A data-driven approach to predicting successes and failures of clinical trials. *Cell chemical biology, 23*(10), 1294-1301.
79. Polykovskiy, D., Zhebrak, A., Vetrov, D., Ivanenkov, Y., Aladinskiy, V., Mamoshina, P., ... & Kadurin, A. (2018). Entangled conditional adversarial autoencoder for de novo drug discovery. *Molecular pharmaceutics, 15*(10), 4398-4405.
80. Stokes, J. M., Yang, K., Swanson, K., Jin, W., Cubillos-Ruiz, A., Donghia, N. M., ... & Collins, J. J. (2020). A deep learning approach to antibiotic discovery. *Cell, 180*(4), 688-702.
81. Zhavoronkov, A., Ivanenkov, Y. A., Aliper, A., Veselov, M. S., Aladinskiy, V. A., Aladinskaya, A. V., ... & Aspuru-Guzik, A. (2019). Deep learning enables rapid identification of potent DDR1 kinase inhibitors. *Nature biotechnology, 37*(9), 1038-1040.
82. Goodfellow, J. et al. (2014). Generative adversarial nets. Adv. Neural Inf. Process.
83. Kadurin, A., Aliper, A., Kazennov, A., Mamoshina, P., Vanhaelen, Q., Khrabrov, K., & Zhavoronkov, A. (2017). The cornucopia of meaningful leads: Applying deep adversarial autoencoders for new molecule development in oncology. *Oncotarget, 8*(7), 10883.
84. Durant, J. L., Leland, B. A., Henry, D. R., & Nourse, J. G. (2002). Reoptimization of MDL keys for use in drug discovery. *Journal of chemical information and computer sciences, 42*(6), 1273-1280.
85. Weininger, D. (1988). SMILES, a chemical language and information system. 1. Introduction to methodology and encoding rules. *Journal of chemical information and computer sciences, 28*(1), 31-36.
86. Akutsu, T., & Nagamochi, H. (2013). Comparison and enumeration of chemical graphs. *Computational and structural biotechnology journal, 5*(6), e201302004.
87. Putin, E., Asadulaev, A., Vanhaelen, Q., Ivanenkov, Y., Aladinskaya, A. V., Aliper, A., & Zhavoronkov, A. (2018). Adversarial threshold neural computer for molecular de novo design. *Molecular pharmaceutics, 15*(10), 4386-4397.
88. Kuzminykh, D., Polykovskiy, D., Kadurin, A., Zhebrak, A., Baskov, I., Nikolenko, S., ... & Zhavoronkov, A. (2018). 3D molecular representations based on the wave transform for convolutional neural networks. *Molecular pharmaceutics, 15*(10), 4378-4385.
89. Polykovskiy, D., Zhebrak, A., Sanchez-Lengeling, B., Golovanov, S., Tatanov, O., Belyaev, S., ... & Zhavoronkov, A. (2020). Molecular sets (MOSES): a benchmarking platform for molecular generation models. *Frontiers in pharmacology, 11,* 565644.
90. Zhavoronkov, A., Vanhaelen, Q., & Oprea, T. I. (2020). Will artificial intelligence for drug discovery impact clinical pharmacology?. *Clinical Pharmacology & Therapeutics, 107*(4), 780-785.
91. AlQuraishi, M. (2019). AlphaFold at CASP13. *Bioinformatics, 35*(22), 4862-4865.
92. Walters, W. P., & Murcko, M. (2020). Assessing the impact of generative AI on medicinal chemistry. *Nature biotechnology, 38*(2), 143-145.
93. Lavecchia, A., & Cerchia, C. (2016). In silico methods to address polypharmacology: current status, applications and future perspectives. *Drug discovery today, 21*(2), 288-298.

94. Baldi, A. (2010). Computational approaches for drug design and discovery: An overview. *Systematic reviews in Pharmacy, 1*(1), 99.
95. Smith, J. S., Roitberg, A. E., & Isayev, O. (2018). Transforming computational drug discovery with machine learning and AI. *ACS medicinal chemistry letters, 9*(11), 1065-1069.
96. Jing, Y., Bian, Y., Hu, Z., Wang, L., & Xie, X. Q. S. (2018). Deep learning for drug design: an artificial intelligence paradigm for drug discovery in the big data era. *The AAPS journal, 20,* 1-10.
97. Vatansever, S., Schlessinger, A., Wacker, D., Kaniskan, H. Ü., Jin, J., Zhou, M. M., & Zhang, B. (2021). Artificial intelligence and machine learning-aided drug discovery in central nervous system diseases: State-of-the-arts and future directions. *Medicinal research reviews, 41*(3), 1427-1473.
98. Blasiak, A., Khong, J., & Kee, T. (2020). CURATE. AI: optimizing personalized medicine with artificial intelligence. *SLAS TECHNOLOGY: Translating Life Sciences Innovation, 25*(2), 95-105.
99. Kilinc, D., Schwab, J., Rampini, S., Ikpekha, O. W., Thampi, A., Blasiak, A., ... & Lee, G. U. (2016). A microfluidic dual gradient generator for conducting cell-based drug combination assays. *Integrative Biology, 8*(1), 39-49.
100. Pease-Raissi, S. E., Pazyra-Murphy, M. F., Li, Y., Wachter, F., Fukuda, Y., Fenstermacher, S. J., ... & Segal, R. A. (2017). Paclitaxel reduces axonal Bclw to initiate IP3R1-dependent axon degeneration. *Neuron, 96*(2), 373-386.
101. Yang, Z., Li, F., Yelamanchili, D., Zeng, Z., Rosales, C., Youker, K. A., ... & Li, Z. (2019). Vulnerable Atherosclerotic Plaque Imaging by Small‐Molecule High‐Affinity Positron Emission Tomography Radiopharmaceutical. *Advanced Therapeutics, 2*(8), 1900005.
102. Zhang, X., Chen, X., Wang, H. Y., Jia, H. R., & Wu, F. G. (2019). Supramolecular nanogel‐based universal drug carriers formed by "soft–hard" co‐assembly: Accurate cancer diagnosis and hypoxia‐activated cancer therapy. *Advanced Therapeutics, 2*(5), 1800140.
103. Badruddoza, A. Z. M., Gupta, A., Myerson, A. S., Trout, B. L., & Doyle, P. S. (2018). Low energy nanoemulsions as templates for the formulation of hydrophobic drugs. *Advanced Therapeutics, 1*(1), 1700020.
104. Rahmatizadeh, S., Valizadeh-Haghi, S., & Dabbagh, A. (2020). The role of artificial intelligence in management of critical COVID-19 patients. *Journal of Cellular & Molecular Anesthesia, 5*(1), 16-22.
105. Monteiro, C. F., Custódio, C. A., & Mano, J. F. (2019). Three‐Dimensional Osteosarcoma Models for Advancing Drug Discovery and Development. *Advanced Therapeutics, 2*(3), 1800108.
106. Kim, S., Cho, A. N., Min, S., Kim, S., & Cho, S. W. (2019). Organoids for advanced therapeutics and disease models. *Advanced Therapeutics, 2*(1), 1800087.
107. M. W. Gifari, P. Samodro, and D. W. Kurniawan, "ARTICLE HISTORY Artificial Intelligence toward Personalized Medicine," PSR.
108. Awwalu, J., Garba, A. G., Ghazvini, A., & Atuah, R. (2015). Artificial intelligence in personalized medicine application of AI algorithms in solving personalized medicine problems. *International Journal of Computer Theory and Engineering, 7*(6), 439.
109. Sotoudeh, H., Shafaat, O., Bernstock, J. D., Brooks, M. D., Elsayed, G. A., Chen, J. A., ... & Friedman, G. K. (2019). Artificial intelligence in the management of glioma: era of personalized medicine. *Frontiers in oncology, 9*, 768.
110. Chakravarty, K., Antontsev, V., Bundey, Y., & Varshney, J. (2021). Driving success in personalized medicine through AI-enabled computational modeling. *Drug Discovery Today, 26*(6), 1459-1465.
111. Lee, D. K., Chang, V. Y., Kee, T., Ho, C. M., & Ho, D. (2017). Optimizing combination therapy for acute lymphoblastic leukemia using a phenotypic personalized medicine digital health platform: Retrospective optimization individualizes patient regimens to maximize efficacy and safety. *Slas Technology: Translating Life Sciences Innovation, 22*(3), 276-288.
112. Briganti, G., & Le Moine, O. (2020). Artificial intelligence in medicine: today and tomorrow. *Frontiers in medicine, 7*, 27.
113. Brody, H. (2013). Medical imaging. *Nature, 502*(7473), S81-S81.
114. Wang, S., Cao, G., Wang, Y., Liao, S., Wang, Q., Shi, J., ... & Shen, D. (2021). Review and prospect: artificial intelligence in advanced medical imaging. *Frontiers in Radiology, 1,* 781868.
115. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *nature, 521*(7553), 436-444.
116. Zhou, L. Q., Wang, J. Y., Yu, S. Y., Wu, G. G., Wei, Q., Deng, Y. B., ... & Dietrich, C. F. (2019). Artificial intelligence in medical imaging of the liver. *World journal of gastroenterology, 25*(6), 672.
117. Panayides, A. S., Amini, A., Filipovic, N. D., Sharma, A., Tsaftaris, S. A., Young, A., ... & Pattichis, C. S. (2020). AI in medical imaging informatics: current challenges and future directions. *IEEE journal of biomedical and health informatics, 24*(7), 1837-1857.
118. Ambinder, E. P. (2005). A history of the shift toward full computerization of medicine. *Journal of oncology practice, 1*(2), 54.
119. Castellino, R. A. (2005). Computer aided detection (CAD): an overview. *Cancer Imaging,* 5(1), 17.
120. Gatos, I., Tsantis, S., Spiliopoulos, S., Karnabatidis, D., Theotokas, I., Zoumpoulis, P., ... & Kagadis, G. C. (2017). A machine-learning algorithm toward color analysis for chronic liver disease classification, employing ultrasound shear wave elastography. *Ultrasound in medicine & biology, 43*(9), 1797-1810.
121. Miotto, R., Wang, F., Wang, S., Jiang, X., & Dudley, J. T. (2018). Deep learning for healthcare: review, opportunities and challenges. *Briefings in bioinformatics, 19*(6), 1236-1246.
122. Shen, D., Wu, G., & Suk, H. I. (2017). Deep learning in medical image analysis. *Annual review of biomedical engineering, 19,* 221-248.
123. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & Sánchez, C. I. (2017). A

survey on deep learning in medical image analysis. *Medical image analysis, 42,* 60-88.
124. Food and Drug Administration. (2019). Proposed regulatory framework for modifications to artificial intelligence/ machine learning (AI/ML)-based software as a medical device (SaMD).
125. Alexander, A., Jiang, A., Ferreira, C., & Zurkiya, D. (2020). An intelligent future for medical imaging: a market outlook on artificial intelligence for medical imaging. *Journal of the American College of Radiology, 17*(1), 165-170.
126. Bala, S. A., Kant, S., & Kumar, K. (2019). Impact of deep learning in medical imaging: a systematic new proposed model. *International Journal of recent technology and engineering,* 112-118.
127. Ahmad, H. M., Khan, M. J., Yousaf, A., Ghuffar, S., & Khurshid, K. (2020). Deep learning: a breakthrough in medical imaging. *Current Medical Imaging, 16*(8), 946-956.
128. Ting, D. S., Liu, Y., Burlina, P., Xu, X., Bressler, N. M., & Wong, T. Y. (2018). AI for medical imaging goes deep. *Nature medicine, 24*(5), 539-540.
129. Oren, O., Gersh, B. J., & Bhatt, D. L. (2020). Artificial intelligence in medical imaging: switching from radiographic pathological data to clinically meaningful endpoints. *The Lancet Digital Health, 2*(9), e486-e488.