Intelligence-Based Medicine 12 (2025) 100267

Contents lists available at ScienceDirect

Intelligence-Based Medicine

journal homepage: www.sciencedirect.com/journal/intelligence-based-medicine

Nanotechnology and machine learning: a promising confluence for the advancement of precision medicine

Shuaibu Saidu Musa [a,b], Adamu Muhammad Ibrahim [c], Muhammad Yasir Alhassan [d], Abubakar Hafs Musa [e], Abdulrahman Garba Jibo [f], Auwal Rabiu Auwal [g,h], Olalekan John Okesanya [i,j], Zhinya Kawa Othman [k], Muhammad Sadiq Abubakar [l], Mohamed Mustaf Ahmed [m,*], Carina Joane V. Barroso [n], Abraham Fessehaye Sium [o], Manuel B. Garcia [p,q,r], James Brian Flores [s], Adamu Safiyanu Maikifi [t], M.B.N. Kouwenhoven [u], Don Eliseo Lucero-Prisno [v,w,x]

[a] School of Global Health, Faculty of Medicine, Chulalongkorn University, Bangkok, Thailand
[b] Department of Nursing Science, Ahmadu Bello University, Zaria, Nigeria
[c] Department of Immunology, School of Medical Laboratory Science, Usmanu Danfodiyo University, Sokoto, Nigeria
[d] Department of Public Health, Symbiosis Institute of Health Sciences, Symbiosis International (Deemed University), Pune, India
[e] Graduate School Nanoscience and Technology, Chulalongkorn University, Bangkok, Thailand
[f] Department of Industrial Pharmacy, Faculty of Pharmaceutical Sciences, Chulalongkorn University, Bangkok Thailand
[g] Department of Biochemistry, Chulalongkorn University Bangkok, Thailand
[h] Department of Biochemistry Aliko Dangote University of Science and Technology, Wudil, Nigeria
[i] Department of Public Health and Maritime Transport, University of Thessaly, Volos, Greece
[j] Department of Medical Laboratory Science, Neuropsychiatric Hospital, Aro, Abeokuta, Ogun State, Nigeria
[k] Department of Pharmacy, Kurdistan Technical Institute, Sulaymaniyah, Kurdistan Region, Iraq
[l] Department of Public Health, Ahmadu Bello University, Zaria, Nigeria
[m] Faculty of Medicine and Health Sciences, SIMAD University, Mogadishu, Somalia
[n] Bukidnon State University, Malaybalay City, Bukidnon, Philippines
[o] Department of Obstetrics and Gynecology, St. Paul's Hospital Millennium Medical College, Addis Ababa, Ethiopia
[p] University of the Philippines Diliman, Quezon City, Philippines
[q] FEU Institute of Technology, Manila, Philippines
[r] Korea University, Seoul, South Korea
[s] College of Computer Studies and Information Technology, Southern Leyte State University, Sogod, Southern Leyte, Philippines
[t] Department of Pharmaceutics and Industrial Pharmacy, Chulalongkorn University, Bangkok, Thailand
[u] Department of Physics, Xi'an Jiaotong-Liverpool University, Suzhou, China
[v] Department of Global Health and Development, London School of Hygiene and Tropical Medicine, London, United Kingdom
[w] Research and Innovation Office, Biliran Province State University, Naval, Biliran Province, Philippines
[x] Center for Research and Development, Cebu Normal University, Cebu City, Philippines

ARTICLE INFO

Keywords:
Nanotechnology
Machine learning
Precision medicine
Drug delivery
Diagnostics
Artificial intelligence

ABSTRACT

The fusion of molecular-scale engineering in nanotechnology with machine learning (ML) analytics is reshaping the field of precision medicine. Nanoparticles enable ultrasensitive diagnostics, targeted drug and gene delivery, and high-resolution imaging, whereas ML models mine vast multimodal datasets to optimize nanoparticle design, enhance predictive accuracy, and personalize treatment in real-time. Recent breakthroughs include ML-guided formulations of lipid, polymeric, and inorganic carriers that cross biological barriers; AI-enhanced nano-sensors that flag early disease from breath, sweat, or blood; and nanotheranostic agents that simultaneously track

* Corresponding author.

E-mail addresses: shuaibusmusa2@gmail.com (S.S. Musa), amuhammadibrahim37@gmail.com (A.M. Ibrahim), alhassanmuhammadyasir@gmail.com (M.Y. Alhassan), hafsbnabuhafs@gmail.com (A.H. Musa), abdulrahmanjibo@gmail.com (A.G. Jibo), auwalrabiu31@gmail.com (A.R. Auwal), okesanyaolalekanjohn@gmail.com (O.J. Okesanya), zhinya.kawa@kti.edu.iq (Z.K. Othman), mohdsadiq.abk@gmail.com (M.S. Abubakar), momustafahmed@simad.edu.so (M.M. Ahmed), carinajoane_barroso@buksu.edu.ph (C.J.V. Barroso), abrahamfessehaye4@gmail.com (A.F. Sium), mbgarcia@feutech.edu.ph (M.B. Garcia), jflores@southernleytestateu.edu.ph (J.B. Flores), safimkf@gsu.edu.ng (A.S. Maikifi), t.kouwenhoven@xjtlu.edu.cn (M.B.N. Kouwenhoven), don-eliseo.lucero-prisno@lshtm.ac.uk (D.E. Lucero-Prisno).

https://doi.org/10.1016/j.ibmed.2025.100267
Received 15 April 2025; Received in revised form 30 May 2025; Accepted 1 June 2025
Available online 10 June 2025

and treat tumors. Comparative insights into Retrieval-Augmented Generation and supervised learning pipelines reveal distinct advantages for nanodevice engineering across diverse data environments. An expanded focus on explainable AI tools, such as SHAP, LIME, Grad-CAM, and Integrated Gradients, highlights their role in enhancing transparency, trust, and interpretability in nano-enabled clinical decisions. A structured narrative review method was applied, and key ML model performances were synthesized to strengthen analytical clarity. Emerging biodegradable nanomaterials, autonomous micro-nanorobots, and hybrid lab-on-chip systems promise faster point-of-care decisions but raise pressing questions about data integrity, interpretability, scalability, regulation, ethics, and equitable access. Addressing these hurdles will require robust data standards, privacy safeguards, interdisciplinary R&D networks, and flexible approval pathways to translate bench advances into bedside benefits for patients. This review synthesizes the current landscape, critical challenges, and future directions at the intersection of nanotechnology and ML in precision medicine.

1. Introduction

The interplay between machine learning (ML) and nanotechnology, which is principally based on the combination of data-driven intelligence with molecular-level accuracy to improve healthcare outcomes, diagnosis, and treatment, has revolutionized the field of precision medicine. The sequencing of the human genome initially increased the demand for rapid progress in clinical medicine by facilitating more precise therapeutics through an understanding of the genetic basis of illnesses [1]. The expression the right care, for the right patient, at the right time is frequently used to characterize individualized strategies for the prevention and treatment of diseases that consider individual variations in genetics, environment, and lifestyle [2]. Precision medicine indicates a transition from disease treatment to individualized patient care using a data-driven, tailored methodology facilitated by developments in big data and omics. It incorporates many types of data, including genomic, epigenetic, environmental, lifestyle, and medical history data, to develop a virtual patient model. Predictive modeling utilizing these interactions seeks to identify or forecast diseases, deliver accurate diagnoses, and improve treatment optimization to emphasize accuracy, cost-effectiveness, and swiftness, with a focus on individualized healthcare solutions [3,4].

Moreover, the incorporation of modern technologies, including nanotechnology, is crucial for the complete realization of the promise of precision medicine. Nanotechnology involves manipulating materials to exploit the unique physical and chemical properties that emerge at the nanoscale (1–100 nm). These properties differ significantly from those of bulk materials, allowing for innovative applications in various fields [5], including precision medicine. The capacity to design nanoparticles, nanocarriers, and nanosensors for interaction with biological systems at the molecular level continues to drive advancements in personalized medicine [6]. The significance of nanotechnology in healthcare lies in its ability to transform diagnostics, drug delivery, and therapies by providing remarkable accuracy in targeting specific cells, tissues, or disease pathways. Metallic nanoparticles, including gold (AuNPs), silver (AgNPs), iron (FeNPs), and polymeric variants, have been thoroughly investigated for their diagnostic capabilities in precision medicine, enabling accurate assessment of patient-specific genes and supporting high-precision diagnoses and tailored treatment strategies [7].

Similarly, the extensive implementation of precision medicine has been significantly improved by recent advances, including computational methods such as artificial intelligence (AI) for managing and analyzing large datasets. Therefore, ML, a subset of AI, can assist in various stages of precision medicine, including data collection, metabolic phenotyping, patient stratification, and the establishment of targeted or combination therapies, while minimizing side effects and implications, thus significantly lowering healthcare expenditures [8–10]. For instance, an AI approach for genome sequence analysis attained high accuracy in disease classification by employing a gene-based screening technique utilizing ML algorithms that efficiently distinguished between pneumonia and COVID-19 [4]. Furthermore, ML algorithms such as Support Vector Machines (SVM), Random Forests, and DL techniques, including Convolutional Neural Networks (CNN) [11], have been successful in diagnosing diseases such as diabetic retinopathy and cardiovascular conditions by analyzing medical imaging data [12]. This extends to clinical decision support systems, where algorithms predict patient outcomes by continuously learning from new data, which is particularly valuable in resource-limited settings. In addition, DL models such as K-Nearest Neighbors (KNN) have been effectively used to analyze voice samples to detect disease, showcasing the versatility of ML across different types of patients. It has also been observed that artificial neural networks (ANN) have good effects on predicting heart diseases [13]. Multiple Linear Regression, Decision Tree Regression, Random Forest Regression and Support Vector Regression algorithms can detect early signs of epidemics by identifying patterns in health data, enabling timely interventions, and reducing the spread of diseases such as dengue and chikungunya. This review explores the integration of nanotechnology and ML in the evolution of precision medicine, emphasizing their current applications and underscoring their transformative potential for improving disease diagnosis, treatment, and patient satisfaction. It also addresses the limitations and ethical implications of their implementation in clinical settings.

2. Methodology

An extensive narrative review was conducted using the Scopus, PubMed, and Google Scholar databases, along with targeted searches from trustworthy online sources, to identify relevant studies on nanotechnology, machine learning, and precision medicine. These databases were chosen because of their comprehensive scope, citation features, and emphasis on scientific literature. Web of Science (WoS) and Embase were omitted because of subscription limitations, overlap with Scopus, and discipline-specific restrictions of the other databases. A total of 131 articles were assessed in this review. The Boolean operators "AND" and "OR" were used to generate detailed search queries such as: ("nanotechnology") AND ("machine learning") AND ("precision medicine OR personalized medicine"). To ensure uniformity and a thorough compilation of pertinent articles, these search terms were consistently applied across all databases. Eligible papers included original research, systematic and narrative reviews, meta-analyses, viewpoints, commentaries, and gray literature. Although no specific publication timeframe was imposed, studies published in the last ten years written in English were prioritized. Exclusions were made for Publications not in English, those without full-text access, and those that did not align with the study's objectives were excluded. A snowballing bibliometric approach was employed to identify additional relevant literature. All articles were assessed for quality, favoring studies that are often cited and have strong methodologies. Studies with poor methods or lacking data were excluded. Considering the scope of this narrative review, only articles pertinent to the research goals were considered. The findings were critically analyzed and organized in a narrative format under appropriate subheadings.

3. Applications of nanotechnology and machine learning in precision medicine

3.1. Diagnostics and early detection

Nanosensors possess the capability to detect biomarkers at very low concentrations, facilitating the diagnosis of diseases such as cancer through markers such as CA 15–3, HER2, BRCA1/2, CEA, and CYFRA 21–1, as well as neurological disorders via markers such as β-amyloid and Tau Protein Levels, EEG alterations, and Thyroid Hormone Levels (T3, T4) [Table 1] [14]. Additionally, nanosensors use materials such as gold nanoparticles and graphene to detect biomarkers at previously undetectable concentrations, thereby improving the early detection of diseases [15].

For example, one study found that gold nanoparticles (NPs) can detect viral infections caused by Flaviviridae, Coronaviridae, Herpesviridae, and Orthomyxoviridae [16]. The same study reported the detection of viruses, such as Human Immunodeficiency Virus (HIV), Hepatitis B Virus (HBV), Hepatitis C Virus (HCV), and Respiratory Syncytial Virus (RSV), as well as bacteria, such as E. coli and M. tuberculosis, using quantum dots (QDs). Furthermore, silver nanoclusters and carbon dots can be used to detect pathogen DNA and Gram-positive bacteria (GPB), respectively [17]. Microbubbles are also used in ultrasonic imaging for tumor detection [18].

Moreover, the early and accurate detection of infectious diseases and neurological disorders using nanotechnology has been enhanced by ML [19,20], where complex datasets from nanodevices are processed using ML algorithms [14]. Techniques such as decision trees and neural networks have demonstrated superior performance in identifying cancer subtypes and predicting treatment responses [21]. Additionally, weakly supervised transfer learning can create personalized models to predict tumor characteristics based on limited patient data, facilitating the development of customized treatment strategies [22]. Therefore, the combination of ML with nanosensor data allows for real-time analysis and personalized treatment plans, significantly improving patient outcomes [21,23].

3.2. Personalized drug delivery

Nanoparticles are increasingly recognized for their potential as targeted drug delivery systems. They enhance therapeutic efficacy while minimizing side effects by carrying and releasing therapeutic agents at specific target sites within the body (Table 1) [24]. The distinct characteristics of nanoparticles, including their size, surface charge, and functionalization, contribute to improved permeability and retention (EPR) effects, which are advantageous for targeting cancerous tissues (Table 2). For example, nanoscale polysaccharide derivatives used as carriers for small interfering RNA (siRNA) have shown potential in osteosarcoma treatment, illustrating the capability of nanoparticles to enable the targeted delivery of genetic therapies. Furthermore, actively targeted nanomedicines have been developed to improve therapeutic efficacy using ligands that specifically bind to cancer cell markers, thereby improving the precision of drug delivery [25]. Therefore, the design of these nanoparticles can be tailored to improve their interactions with biological systems, such as through the engineering of lipid-based, polymeric, and inorganic nanoparticles, which allows the

Table 1
Applications of nanotechnology and machine learning in precision medicine.

Application Area	Key Features & Technologies	Examples & Outcomes
Diagnostics & Early Detection	• Nanosensors for ultralow biomarker detection • ML algorithms (DL, KNN, Random Forest) for prediction • Gold nanoparticles, QDs, graphene for viral & bacterial detection	• Detection of cancer, neurological & infectious diseases • Improved diagnostic accuracy using ML + nano-biosensors
Personalized Drug Delivery	• Nanocarriers for targeted delivery (e.g., lipid, polymeric, inorganic) • AI for drug design & optimization- Controlled & sustained release	• Enhanced bioavailability of drugs like Olaparib • Reduced systemic toxicity in cancer & autoimmune therapy
Advanced Imaging Techniques	• Nanoparticles as contrast agents in MRI, PET, CT • AI for image analysis and tumor tracking- Theranostic nanoprobes	• Real-time tumor monitoring • Enhanced precision in cancer detection and therapy
Real-Time Patient Monitoring	• Nanosensors for physiological tracking (e. g., glucose, HR variability) • AI prediction of health risks Customizable wearable devices	• Early intervention and preventive care Personalized monitoring of chronic conditions
Gene Therapy & Editing	• Nanoparticles for CRISPR delivery • ML to reduce off-target effects • Tools like CRISPR for prediction	• Increased safety and precision of gene editing • Improved delivery and efficacy of gene therapy
Biomedical Applications	• ML models for nanomaterial toxicity prediction • Wearables, voice-to-text, gesture control • ML for gas/pollutant/ biomarker detection	• Real-time environmental & health monitoring • Safer nanomaterial development & advanced HMI (human-machine interface) technologies
Case Studies	• AI-integrated nanosensors in sweat, breath, saliva, blood • Nanosensor arrays, QDs, transistor sensors • Deep learning for lesion detection	• Early cancer diagnosis (e.g., VOC detection) • Brain metastasis detection with 98.7 % accuracy • AIoT systems for smart healthcare

Table 2
Comparison of conventional and ML-Driven nanomedical approaches.

Domain	Conventional Nanomedicine	ML-Driven Nanomedicine
Diagnostics & Early Detection	Utilizes nanosensors (e.g., gold NPs, QDs) to detect biomarkers (e.g., CA15-3, BRCA1/2) at low concentrations.	ML algorithms (e.g., DL, RF, SVM) predict tumor characteristics, personalize diagnostics, and analyze nanosensor data in real time.
Personalized Drug Delivery	Nanocarriers (e.g., liposomes, siRNA-based NPs) for targeted delivery to improve bioavailability and reduce toxicity.	ML models analyze omics data to optimize drug targeting, predict responses, and design adaptive drug release mechanisms.
Advanced Imaging	Nanoparticles as contrast agents in MRI, CT, and PET scans; static imaging applications.	ML enables real-time analysis of imaging data (e.g., PET, MRI), enhances diagnostic accuracy, and supports treatment response monitoring.
Real-Time Patient Monitoring	Nanosensors used to measure vitals (e.g., glucose, HR) continuously; basic data interpretation.	AI-powered nanosensors predict disease events (e.g., cardiac episodes), tailor interventions based on dynamic data.
Gene Therapy & Editing	Nanoparticles used to deliver CRISPR components for gene editing; basic targeting.	ML predicts off-target effects, refines CRISPR delivery, and enhances precision in genomic applications (e.g., CRISPOR tools).
Biomedical Applications	Wearable nanosensors for basic health and environmental monitoring; toxicity assessed via traditional assays.	ML predicts nanomaterial toxicity, optimizes wearable interface designs (e.g., QLEDs), and supports real-time environmental diagnostics.

customization of drug release profiles and targeting mechanisms, which is crucial for achieving personalized treatment. [26]. In addition, nanocarriers are designed to transport drugs to specific cells or tissues, thereby improving treatment precision. They are often used to enhance the solubility and stability of drugs, improve their bioavailability, and allow for controlled and sustained release [24].

Moreover, the application of nanotechnology in drug delivery systems has been shown to significantly enhance the therapeutic index of anticancer agents, thereby reducing systemic toxicity and improving patient compliance [27]. Olaparib (Ola) is an anticancer agent that functions by inhibiting poly (ADP-ribose) polymerase (PARP), a critical enzyme involved in DNA damage repair. The drug exhibits poor absorption in the gastrointestinal tract (GIT) owing to its physicochemical characteristics, which restrict its efficacy and therapeutic potential. However, encapsulating it in a liposphere, a nanoparticle delivery technology, mitigates these problems by enhancing the drug's solubility and stability and facilitating its passage through the GIT more efficiently. Additionally, encapsulation improves the oral bioavailability of the medicine, resulting in a higher percentage of the drug entering systemic circulation, thereby enhancing its therapeutic efficacy [28]. In autoimmune diseases, nanotechnology facilitates the targeted delivery of immunomodulatory agents, which can be tailored to the specific immune profiles of patients, thus improving treatment outcomes and reducing side effects [29].

Moreover, by analyzing omics data, such as genomes, metabolomics, and proteomics, ML algorithms can identify biomarkers associated with disease pathways and therapeutic outcomes, which aids in guiding the choice of the most effective drug targets and therapeutic strategies [19, 30]. Additionally, nanoparticle delivery efficiency to tumors can be predicted using ML algorithms such as DL, linear regression, K-nearest neighbors, and random forest. ML-developed nanoparticle-based formulations, such as Vyxeos and Hensify, work synergistically to combine active pharmaceutical ingredients for improved therapeutic results [31, 32]. The analysis of the microenvironment, where ML and nanotechnology describe tumor development, metastasis, and response to therapy, has enabled more efficient and personalized care [33]. AI-powered nanomedicine devices that enable real-time drug administration, pharmacokinetics, and therapeutic response monitoring are equally important, as they facilitate customizable therapy regimens and improve patient outcomes [34]. For example, DNA logic circuits have been used to create responsive nanomedicines that can adjust their therapeutic actions based on specific biomarkers present in tumors, thus enhancing the precision of cancer therapy [35]. This enables the creation of intelligent drug delivery systems that can dynamically respond to changes in the tumor microenvironment.

3.3. Advanced imaging techniques

Nanotechnology has revolutionized imaging modalities by providing enhanced contrast agents and imaging probes that improve the sensitivity and specificity of magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET) [36], thereby allowing more precise imaging of tumors and other pathological conditions. For example, superparamagnetic iron oxide nanoparticles have been used to enhance MRI contrast, allowing better visualization of tumor margins. When combined with theragnostic nanoprobes, this yields simultaneous imaging and targeted therapy [35–37].

Moreover, ML is transforming brain tumor screening and detection by collecting image features such as structure, grayscale, and texture, and using classifiers such as random forests, SVM, and KNN to enhance efficiency and accuracy [32,38]. For example, ML techniques have been used to analyze data from PET scans, allowing the identification of metabolic changes associated with tumor progression or response to therapy [39,40]. Furthermore, ML can improve the interpretation of multimodal imaging data from nanodevices by integrating information from various imaging techniques to provide a comprehensive view of the disease status. This capability is particularly valuable in oncology, where the combination of imaging modalities can produce a more accurate assessment of the tumor burden and treatment response. By automating imaging data analysis, ML algorithms can reduce the time required for interpretation and improve the consistency of diagnostic assessments, ultimately leading to better outcomes. Therefore, the combination of nanomaterials and AI in imaging not only improves the detection of malignancies but also aids in monitoring treatment responses, making it a crucial component of personalized medicine.

3.4. Real-time patient monitoring

The combination of nanotechnology and ML for real-time patient monitoring marks a significant step forward in precision medicine. Nanodevices, including nanosensors, are being developed for ongoing physiological surveillance, which enables the live tracking of vital signs and biochemical indicators. These devices can identify molecular-level changes and provide essential data for clinical decision making [41, 42]. For instance, nanosensors can track glucose levels in patients with diabetes or identify disease biomarkers, facilitating prompt intervention [43]. In addition, ML algorithms can process large amounts of data generated by these nanodevices, identify patterns, and predict potential health problems before they become critical [44,45]. For example, AI systems can analyze trends in heart rate variability to predict cardiac events, thus facilitating preventive measures [46].

3.5. Gene therapy and editing

In gene therapy and editing, nanoparticles play a crucial role in providing gene-editing tools, such as CRISPR-Cas9 (Table 1). These nanoparticles can encapsulate CRISPR components, improving their stability and facilitating targeted delivery to specific cells and tissues [47,48]. This targeted approach minimizes off-target effects, which are a significant concern in gene editing [49]. Furthermore, ML is instrumental in guiding target identification and reducing off-target effects in gene editing by analyzing genomic data [50]. For example, tools such as CRISPR use ML to assess the likelihood of off-target events, thereby providing researchers with valuable insights that improve the safety and effectiveness of gene editing [51]. This synergy between nanotechnology and ML advances the capabilities of gene therapy and ensures a higher degree of precision and safety in clinical applications [52].

3.6. Biomedical fields

ML models help predict the cytotoxicity of nanomaterials, ensuring their safe application. Large datasets on nanomaterial toxicity are used to train ML models, such as LightGBM and Random Forests, guiding regulatory efforts and predicting safe-by-design nanomaterials [53]. Additionally, ML models are increasingly used to design sensitive and selective NM-based sensors for detecting gases, pollutants, and biomarkers, achieving rapid and accurate public and environmental monitoring and risk assessments [54]. Moreover, ML-driven research on quantum dots and triboelectric nanogenerators is pushing the boundaries of wearable human-machine interfaces, including ML-optimized quantum dot-based light-emitting diodes (QLEDs), voice-to-text conversion devices for hearing aids, and gesture-controlled interfaces for remote device operation [55].

4. Case studies of nanotechnology and ML in precision medicine

Several studies have highlighted the transformative role of nanosensors in early and noninvasive disease detection. Gupta and Basu showed how effective nanosensors can be in the early identification of diseases [56]. They created nanosensors that can identify illnesses without visible signs by mimicking immune responses. These sensors can track tumor growth, detect organ implant contamination, and identify biomarkers. This innovation holds promise for applications in drug delivery systems, personalized healthcare, and early disease diagnosis. Saylan et al. explored non-invasive nanosensors that can identify biomolecules in bodily fluids, such as tears, saliva, and sweat, offering high sensitivity, portability, and low cost. The integration of ML has enhanced these sensors for real-time diagnostics, health status monitoring, and the identification of markers for various conditions [57].

Furthermore, Sahi and Kaushik explored the combination of AI, IoT, and nanotechnology to create AIoT systems that enhance medical devices and operations, while improving data management and medical robotics when used alongside nanotechnology [56]. By combining metal

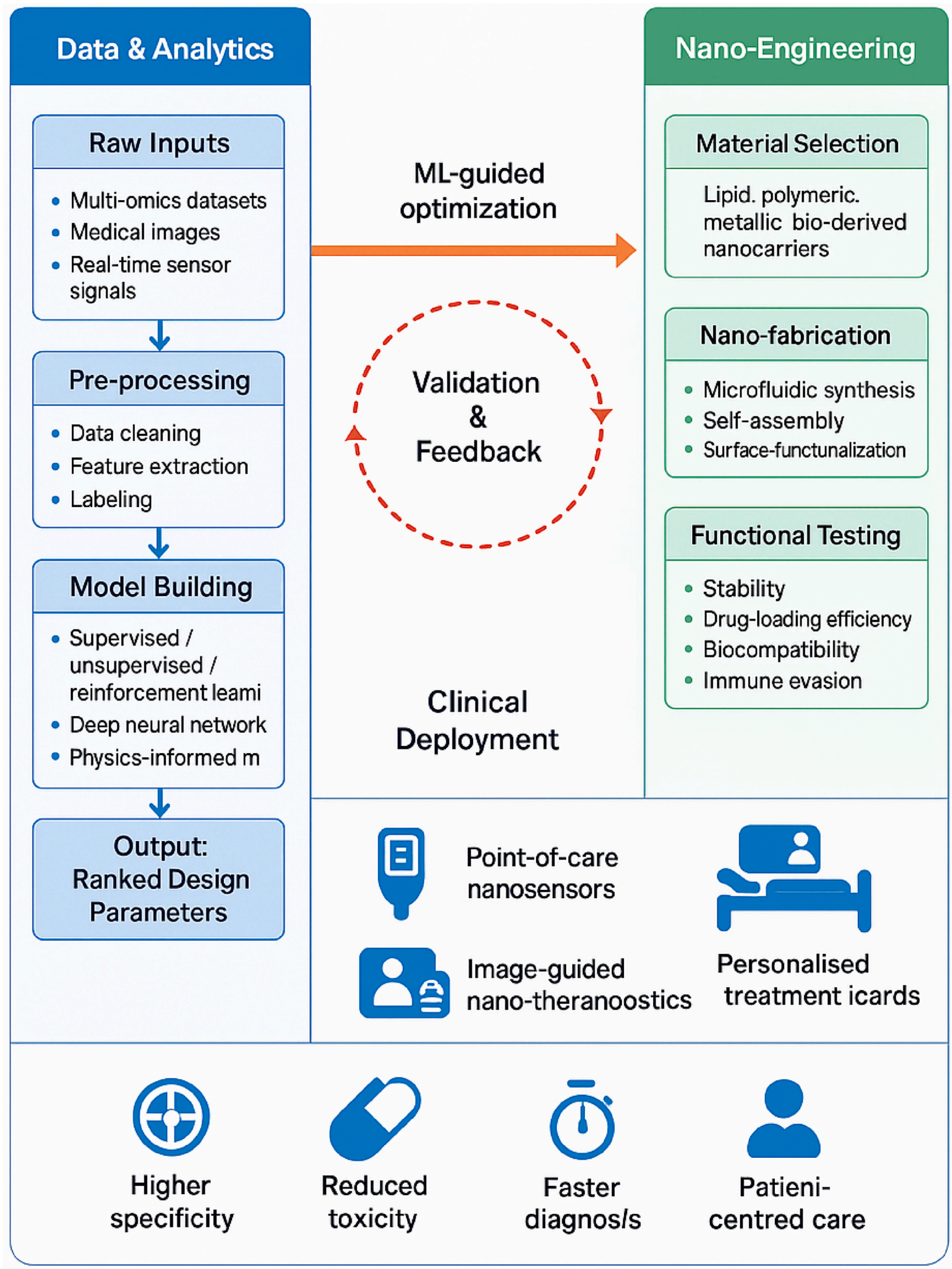

Fig. 1. Synergistic workflow of machine-learning-driven nanotechnology for precision medicine.

oxide nanostructures with protein nanocatalysts, Kim et al. improved the accuracy of breath analysis, a noninvasive diagnostic tool that uses chemical-resistant respiratory sensors. ML can detect disease biomarkers at very low concentrations, making it a promising technology for the early diagnosis of conditions such as cancer and respiratory diseases [58]. Yang et al. developed functional, fast-response time, and specific transistor sensors for detecting diseases such as cancer, viral infections, toxins, and injury markers, making them effective in clinical settings. ML plays a critical role in interpreting and analyzing data from these sensors, allowing precise and rapid clinical decision-making [59]. Another study by Palaniyandi et al. focused on the use of nanosensors to diagnose and treat neurodegenerative diseases such as Alzheimer's disease and inflammatory bowel disease [60]. Rabbani et al. explored the use of nanomaterials, such as carbon nanotubes, graphene, and nanoparticles, to develop flexible biosensors for medical diagnostics, offering reliable and multidimensional performance in disease detection [61]. Mujawar et al. also investigated advanced biosensor technologies using nanotechnology to identify disease biomarkers at extremely low concentrations, enabling early detection of conditions like cancer and infectious diseases and timely interventions [62].

Furthermore, Noah and Ndangili developed point-of-care nanosensors for disease diagnosis, allowing rapid disease detection at the patient's location [63]. Yaari et al. developed an optical nanosensor array combined with ML for protein marker detection in biological fluids, achieving high accuracy and cost-effectiveness [64]. Moreover, Peng et al. used a nanosensor array to detect volatile organic compounds (VOCs) in the breath, distinguishing between healthy individuals and those with various types of cancer. By incorporating ML, these methods have been refined to identify cancer types with higher precision, offering a non-invasive, cost-effective, and early diagnostic tool for various cancers [65]. For small lesions, deep learning algorithms designed by Madhugiri et al. demonstrated a sensitivity of 79.2 % and a positive predictive value of 95.6 %, outperforming manual identification [66]. By attaining a sensitivity and accuracy of 97.5 % and 98.7 %, respectively, Huang et al. considerably improved AI performance and established a new standard for the diagnosis of brain metastases [67].

5. Emerging trends and innovations

The synergistic potential of nanotechnology and ML approaches presents [Fig. 1] opportunities in critical areas of innovation, including hybrid nanotech-ML platforms, predictive and preventive medicine, accelerated drug discovery, and regenerative medicine, with substantial contributions from scientific research and technological breakthroughs [68].

5.1. Hybrid nanotech-ML platforms

Hybrid platforms that combine nanotechnology and ML have redefined the precision of diagnostics and therapeutics. These systems integrate nanobiosensors with embedded AI processors to enable real-time data collection, processing, and decision-making [19]. For instance, through the combination of mass spectrometry and SVM-based feature selection, Wang et al. were able to identify important lipid biomarkers for the early detection of lung cancer, with a sensitivity and specificity of over 90 % and 92 %, respectively [69]. Hollon et al. also presented DeepGlioma, an AI-powered rapid screening tool trained on multimodal datasets in the field of glioma diagnostics, allowing for the rapid identification of molecular changes using methods such as stimulated Raman histology [70].

The ability to embed AI capabilities directly into nanotechnology-based platforms is particularly promising in resource-limited settings, where access to specialized diagnostic tools is scarce. ML-enhanced nanosensors have shown significant potential for the noninvasive monitoring of glucose levels in patients with diabetes, which is a critical advancement in the management of chronic diseases [71]. Additionally, advancements in standard hematological tests have demonstrated their potential in cancer identification. Using ML and plasma degradation profiling, Tsvetkov et al. differentiated patients with glioma from healthy individuals with an accuracy of 92 % [72]. Another example of the expanding potential of AI and nanotechnology-driven diagnostics was demonstrated by Podnar et al., where ML applied to routine blood tests could compete with neuroimaging in brain tumor screening. [73]. Therefore, these integrated systems exemplify the power of convergent technologies in addressing various health needs [74].

5.2. Predictive and preventive medicine

Nanotechnology and ML have significantly advanced disease prediction, diagnosis, and environmental monitoring, particularly during the COVID-19 pandemic, enabling a shift from reactive to proactive healthcare through predictive approaches. DL approaches using recurrent neural networks and long short-term memory (LSTM) have demonstrated high accuracy and low error rates in predicting COVID-19 case increases over 30 days [75]. ML on Kaggle datasets, for instance, has been used to predict virus outbreaks by comparing data from India and China [76]. Hence, predictive models for recovery rates and caseloads have been proposed, suggesting that ML can enhance forecasting accuracy during health crises. Hence, advanced AI models have been critical in medical imaging innovations, improving the diagnostic speed and precision [32,77,78].

Moreover, nanotechnology-based monitoring devices can capture real-time physiological data, and ML-driven analytics can interpret these data to predict the onset and progression of disease (Table 3). This paradigm shift shows promise in combating chronic and lifestyle-related diseases, which account for significant global morbidities and mortalities [79,80]. Pneumonia, for instance, has been detected using DL methods such as CNN variations, including DenseNet, ResNet, and MobileNet [81]. In addition, innovations, including multi-branch learning, ensemble methods, explainable AI tools, and transfer learning, work well with hybrid feature selection methods and transfer learning while withstanding noisy data [82]. Comprehensive datasets for creating predictive radiomic signatures and enhancing early detection are available through programs such as the NLST and LUNGx Challenge [82,83]. It is also worth noting that rapid diagnosis models for COVID-19 have been made possible by pixel-level segmentation and fusion datasets. To improve diagnostic efficiency and accuracy, new diagnostic techniques are being used, such as voting-based ensemble classifiers, social optimization algorithms, and portable thermal imaging systems [84,85].

Moreover, cutting-edge AI approaches have been combined with imaging technologies to enhance the detection and prediction of lung cancer. Lung nodule detection from CT scans has improved via models such as multi-perspective and multi-feature deep fusion learning frameworks [86], where Riesz wavelet transformations and LBP features have improved the diagnostic accuracy in differentiating benign from malignant nodules. Even with small datasets, DL models, particularly DenseNet-121 and transfer learning techniques, have shown promise [87–89]. Significant advancements in nodule detection and malignancy classification have been demonstrated using hybrid approaches, including CNN, genetic algorithms (GA), gray wolf optimization (GWO), and segmentation techniques [82]. Advanced sensor-equipped nanoscale robots controlled by AI algorithms are also being developed for precise cellular illness detection and real-time monitoring, allowing for early intervention, where preliminary diagnostic accuracy is improved by methods such as the Complementary Learning Fuzzy Neural Network (CLFNN), which simulates human-like reasoning [90,91].

Moreover, AI-powered emotion recognition tools are transforming nanomedicine for mental health monitoring and patient-centered care. These technologies use ML techniques to enhance the performance and accuracy of emotion classification, including textual interaction-based emotion estimation and hybrid recommendation systems. Strong

Table 3
A summary of ML model performances in precision medicine.

ML Models	Application area	Performances	References
Support Vector Machines (SVM)	Early lung cancer detection (mass spec + SVM); disease diagnosis; emotion recognition; feature selection	Sensitivity >90 %, specificity 92 % for lung cancer; used for emotion classification with multi-class kernels	[69,97]
Random Forest (RF)	Disease prediction; tumor classification; imaging data analysis	Effective in clinical decision support and diagnostics	[72,97]
Deep Learning (DL)	COVID-19 prediction, lung cancer diagnosis, pneumonia detection, brain metastasis detection	High accuracy; DenseNet, ResNet, MobileNet used for pneumonia; DenseNet-121 for brain metastases detection	[70,87,89]
Convolutional Neural Networks (CNN)	Medical imaging diagnostics (lung cancer, pneumonia); emotion recognition	CNN variations (DenseNet, ResNet, MobileNet) used; hybrid approaches combining CNN with genetic algorithms	[87,88,98]
K-Nearest Neighbors (KNN)	Voice analysis for disease detection; imaging data classification	Used for Parkinson's detection and imaging data analysis	[12,93]
Artificial Neural Networks (ANN)	Heart disease prediction	Good predictive effects reported	[13,96]
Weighted Association Rule-Based Classifiers	Early cardiac failure prediction	User-friendly GUI-based diagnostic tool	[13]
Coactive Neuro-Fuzzy Inference Systems (CANFIS)	Cardiovascular disease prediction	Hybrid system with improved prediction accuracy	[13]
Naïve Bayes Classifiers	Heart disease prediction	Classical ML model enhancing diagnostic accuracy	[13]
Genetic Algorithms (GA)	Lung nodule malignancy classification	Combined with CNN and segmentation methods	[83,98]
Gray Wolf Optimization (GWO)	Lung cancer detection	Used with CNN and segmentation techniques	[83,98]
Complementary Learning Fuzzy Neural Network (CLFNN)	Cellular illness detection	Simulates human-like reasoning to improve diagnostic accuracy	[13]
Hidden Markov Models (HMM)	Emotion detection	Improves accuracy over previous models	[94,95]
Transfer Learning	Lung cancer diagnosis; glioma detection	Used to improve accuracy with small datasets	[70,87]
Ensemble Methods & Voting-Based Classifiers	COVID-19 diagnosis; general diagnostic improvement	Voting-based ensemble classifiers improve accuracy	[88,99]
Self-Supervised Learning Transformers	Multimodal emotion detection	Context-aware model enhancing emotion classification	[92,93]
Multi-class SVM Kernels	Emotion classification	Effective classification of textual emotion data	[94,95]

performance has been demonstrated across various datasets using models such as keyword-based classifiers, hybrid neural networks, and multi-class support vector machine (SVM) kernels [92,93]. Hence, emotional links between words can now be better captured by sophisticated models such as CNN architectures, BiLSTM, and semantic emotion neural networks (SENN). Multimodal emotion detection has also seen the introduction of self-supervised learning transformers and self-attention fusion mechanisms, suggesting a move toward increasingly complex and context-aware models. The accuracy over prior resources such as WordNet-Affect has been further improved by Hidden Markov Models and upgraded knowledge bases such as EmoSenticNet [93–95]. Notably, supervised ML algorithms are increasingly being used to predict and diagnose heart diseases. Graphical User Interfaces (GUIs) using Weighted Association Rule-Based Classifiers are user-friendly diagnostic AI tools that have been successfully applied to improve early cardiac failure prediction [96]. Additionally, Hybrid systems, such as coactive neuro-fuzzy inference systems (CANFIS) and classical ML models, such as Naïve Bayes classifiers, improve prediction accuracy. These advancements demonstrate the growing role of AI in creating smarter, faster, and more accessible tools for cardiovascular health monitoring, diagnosis, and personalized care in nanomedicine [96]. Therefore, the role of predictive analytics in personalizing treatment regimens cannot be overstated, as these technologies facilitate population-level surveillance and identify patterns and trends that guide public health strategies [74].

5.3. Accelerated drug discovery

The drug discovery process has long been plagued by high costs, long timelines, and high attrition rates. The combination of nanotechnology and ML has significantly streamlined this process by enabling the rapid screening, optimization, and development of nanoparticle-based drug formulations. ML algorithms can analyze large datasets to identify promising candidates for therapeutic applications, thereby dramatically reducing the time required for preclinical testing [80]. Additionally, AI-guided nanorobots in drug delivery can target body locations while preserving healthy tissues, increasing therapeutic efficacy, and reducing toxicity and adverse consequences. To optimize individualized treatment, these nanorobots can automatically modify drug release rates in response to physiological data collected in real time [90,100]. A notable area of application is the development of personalized therapeutics for rare diseases, where traditional drug development methods often fail because of limited patient populations. Moreover, Nanotechnology, with its ability to target specific cellular pathways, combined with ML's predictive capabilities of ML, has paved the way for the discovery of precision drug delivery systems. For example, ML models have successfully identified nanoparticles capable of crossing the blood-brain barrier, which is a critical challenge in the treatment of central nervous system disorders [19,101]. Furthermore, ML has been instrumental in optimizing the physicochemical properties of nanocarriers, enhancing their efficacy and safety profiles. This innovation has significant implications for cancer treatment, where the delivery of chemotherapeutic agents to tumor sites with minimal off-target effects is crucial [102].

5.4. Regenerative medicine

In regenerative medicine, the convergence of nanoscale scaffolds and AI-driven optimization strategies has opened new frontiers for tissue engineering and stem cell therapies. Nanotechnology provides tools for designing scaffolds that mimic the extracellular matrix and create an ideal environment for cell growth and differentiation. ML offers predictive models for optimizing scaffold properties and guiding experimental designs [103]. AI has also facilitated advances in stem cell research by analyzing genetic and epigenetic data to predict differentiation outcomes, thus enhancing the precision of regenerative therapies. For instance, cardiac patches have been developed to repair myocardial infarction, and neural tissues have been engineered to treat spinal cord injuries [7,74]. These innovations demonstrate the transformative potential of combining nanotechnology and ML to address some of the most challenging medical conditions worldwide. Moreover, the integration of nanoscale materials with AI has been pivotal in the development of biocompatible and functional prosthetic devices. These technologies have the potential to restore mobility and functionality in patients with disabilities, further highlighting the role of converging technologies in improving patient-centric care [101].

5.5. Comparative AI pipelines for nano-engineering

Two dominant artificial intelligence pipelines currently guide nanodevice design (Fig. 2): (i) Retrieval-Augmented Generation (RAG), which retrieves multi-omics and materials science literature in real time and couples it with a generative large-language model to propose novel carrier chemistries, and (ii) classical supervised or self-supervised prediction pipelines that learn mappings from labelled structure–property datasets to rank candidate nanocarriers [104,105]. RAG excels when published evidence is sparse or rapidly evolving because it grounds generation in the latest external knowledge; however, it inherits a retrieval bias and depends on high-quality embedding [106,107]. Supervised pipelines achieve state-of-the-art accuracy on well-curated physicochemical datasets and integrate physics-informed layers for stability predictions; however, they struggle to extrapolate beyond their training domain. [108,109]. A growing trend is to hybridize both approaches, using a RAG front-end to suggest compositions and a supervised back-end for fast in-silico screening, thereby shortening the design–make–test loop from weeks to hours.

6. Challenges and limitations

6.1. Technical barriers

Integrating nanotechnology devices with ML in precision medicine faces several technical barriers, including data scarcity, bias, and overfitting issues. A significant challenge is the complexity and high heterogeneity of patient data, which complicate the design of diagnostic and therapeutic platforms [19]. Similarly, AI models often rely on large, high-quality datasets that are often incomplete, inconsistent, noisy, or based on Western populations [110]. Multimodal data, including imaging, genetic, and clinical information, must also be fused for personalized nanosystems, which are high-dimensional, platform-dependent, and difficult to integrate [111]. The integration of ML with nanotechnology-based medical sensors is crucial for advanced clinical decision support systems. However, challenges in data privacy, security, and the development of reliable nanoscale IoT devices must be addressed [112]. The scalability of manufacturing AI-optimized nanoparticles is another challenge. Mass production of patient-specific formulations adapted to genetic profiles is difficult. The inconsistent performance of nanoparticles can result from minor changes made during production. Hence, AI tools, such as GANs and workflow optimization models, are being developed to predict feasible designs and streamline production, although the lack of standard protocols hinders reproducibility [113–115]. Although predictive accuracy is critical, clinicians, regulators, and patients must understand why an algorithm recommends a specific nanotherapy. Post hoc, model-agnostic tools such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) assign importance scores to specific design features (e.g., zeta potential, core-shell ratio, or PEGylation), enabling bench scientists to refine these parameters [116,117]. In imaging-based nanodiagnostics, Gradient-weighted Class Activation Mapping (Grad-CAM) and Integrated Gradients highlight the pixel regions or spectral peaks that drive lesion classification, facilitating regulatory review and transparent communication with radiologists [118,119]. For biosensing applications, saliency maps superimposed on impedance spectra or Raman shifts provide real-time calibration cues for point-of-care nanosensors and generate intuitive visuals that clinicians can share with patients and caregivers, meeting the requirements for patient-facing interpretation [120,121]. Embedding these explainability methods into the clinical software stack reinforces trust, satisfies forthcoming transparency provisions in the EU AI Act, and helps mitigate liability concerns.

Moreover, the integration of nanotechnology with AI systems is complex because of the need for precise control and manipulation at the nanoscale, which requires sophisticated algorithms and computational models. [122]. Therefore, successful integration requires a multidisciplinary approach, including materials science, computer engineering, biomedicine, and data science, to develop compatible systems and interfaces [122]. The handling of large and complex datasets from nanosensors also presents challenges. Nanosensors generate vast amounts of complex and multidimensional data, posing challenges in data storage, processing, and analysis [98], as well as autonomous decision-making, which can be provided by ML algorithms. In addition, data standardization, privacy, and the need for collaborative networks for data sharing are significant challenges [123]. The integration of big data analytics with precision medicine also requires the development of robust informatics systems to effectively manage and interpret these datasets [124]. Therefore, advanced ML algorithms capable of efficiently processing and extracting meaningful insights from these large datasets are crucial for real-time decision-making in precision medicine [23].

6.2. Ethics and privacy concerns

The integration of nanotechnology and AI in precision medicine raises significant ethical, privacy, and data-related concerns, particularly regarding data security, genetic data analysis, and interdisciplinary collaboration. This is because breaches of patient privacy can occur, requiring robust computational data protection measures combined with legal and ethical frameworks to ensure secure sharing of genomic data [125]. Additionally, the integration of AI and nanotechnology amplifies the collection of sensitive data, thus increasing the risk of cyberattacks and exposing systems to increased vulnerabilities [126]. Therefore, developing comprehensive regulatory frameworks is critical for protecting patient data and maintaining adherence to privacy legislation [127].

Furthermore, ethical challenges in genetic data analysis, including informed consent, intellectual property rights, privacy, equitable access to innovations, and the handling of incidental findings, require careful ethical considerations, including dynamic consent models that adapt over time [128]. When trained on biased datasets, AI algorithms can reinforce existing biases, resulting in inequitable outcomes in healthcare systems [126]. In addition, the ethical dilemmas surrounding genetic modifications require careful consideration, emphasizing the need to assess the potential implications of these interventions [127].

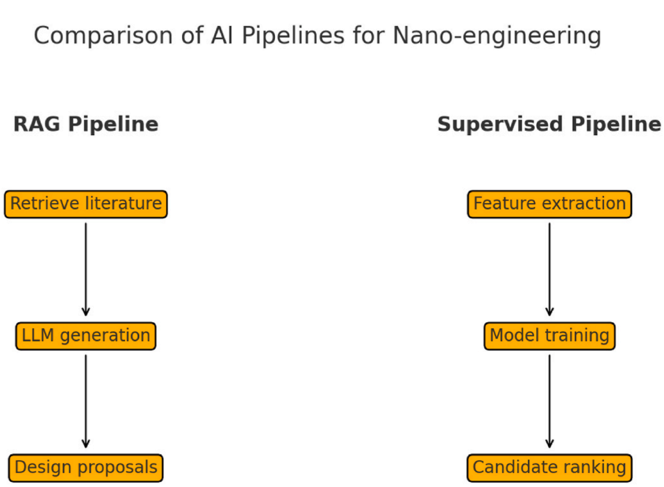

Fig. 2. Comparison of AI pipelines for nano-engineering.

6.3. Cost and accessibility

Developing multifunctional ML platforms for clinical data management and analysis can support personalized medicine, potentially reducing costs by optimizing decision-making and improving patient outcomes [129]. However, the production of nanomaterials and their integration with ML systems involves substantial manufacturing costs, which may pose financial challenges for smaller healthcare providers [23,130]. Furthermore, the development of nanotechnology-ML applications requires significant initial investment in research and development, often necessitating access to specialized facilities and highly skilled expertise [80,91]. The significant costs associated with these technologies also risk widening existing healthcare disparities, restricting access for underprivileged populations, and perpetuating inequality in healthcare delivery [99,131]. Usability challenges, such as interpretability and workflow integration, are also of equal concern. These challenges decrease adoption in practice because AI technologies are not clinician-friendly, have confusing interfaces, and require extensive training [114]. Moreover, innovative treatments incorporating nanotechnology and ML often fall outside the scope of many insurance plans, creating additional barriers to patient access [132].

6.4. Regulatory challenges

Significant regulatory challenges arise when AI and nanotechnology are used in the field of nanomedicine. The dynamic nature and opaqueness of AI algorithms and the complexity of nanomedicines exceed the capabilities of conventional approval processes. [114,133]. For example, the US Food and Drug Administration (FDA) faces challenges in regulating nanotechnology-based products because of the unique properties of NMs, which require specific safety and efficacy evaluations [134]. Additionally, the regulatory pathways for nanomedicine are complex and often lack clear guidelines, which can hinder the approval and clinical adoption of these technologies [135]. Therefore, ensuring biocompatibility and addressing safety concerns are critical for the clinical application of nanotechnology in medicine [136]. Furthermore, regulatory challenges in ML, such as ensuring the generalizability and reliability of predictive models, have been noted, as these models often fail to perform consistently across datasets [137]. There is also a concern that AI could worsen healthcare inequalities because patients and practitioners may find it difficult to understand AI-driven- and data-driven therapy suggestions [138].

7. Future directions

7.1. Innovations on the horizon

The future of biodegradable nanomaterials and environmentally friendly technology appears promising, particularly with the integration of AI systems, such as ML and quantum computing. While biodegradable nanoparticles are used in drug delivery systems [139], biodegradable nanoscale sensors can detect pollutants at low concentrations, providing real-time data for environmental assessments and supporting pollution control efforts (Fig. 1) [91], which are necessary for the mitigation of some respiratory diseases. Additionally, smart nanocarriers that can respond to environmental signals, such as pH or temperature changes, and release their payloads exclusively in the appropriate region are highlighted, as they increase therapeutic effectiveness while reducing systemic drug exposure [2].

Furthermore, ML algorithms analyze massive volumes of patient data to anticipate reactions to specific treatments, allowing personalized therapeutic approaches based on individual genetic profiles and illness characteristics. This could greatly improve the precision of the drug composition [7]. Therefore, ML facilitates the identification of new biomarkers that can guide the development of nanomedicines customized for individual patients, thereby improving diagnosis and treatment strategies [71]. Moreover, future breakthroughs will include advanced lab-on-chip devices that use nanotechnology for fast-track diagnostics. These devices can analyze small blood or tissue samples for early disease detection, providing immediate results that inform treatment decisions [71].

Moreover, multi-omics data integration provides a comprehensive perspective of biological processes by merging information from many omic layers, including genomics, transcriptomics, proteomics, and metabolomics (Fig. 1). This comprehensive approach contributes to our understanding of the complex interactions within biological systems and disease pathways [97]. Additionally, the integration of multi-omics data is critical for precision medicine, which tailors treatments to specific patient profiles based on distinct biological traits. This may lead to more effective medications and improved patient outcomes [140,141]. In oncology, integrated multiomics analyses have led to breakthroughs in understanding cancer biology, enabling better classification of cancer types and prediction of treatment response. ML techniques are being progressively developed to automate this integration process, thereby enabling drug discovery and personalized treatment strategies [140,142]. These innovations represent a significant shift towards more personalized and effective medical treatments through the integration of nanotechnology and ML, paving the way for a new era in precision medicine.

7.2. Collaborative efforts

The synergy between nanotechnology, ML, and healthcare requires rigorous multidisciplinary research and collaboration among key stakeholders in the field. This collaboration is crucial for promoting innovation and driving meaningful application. Therefore, collaboration among the government, academia, and industry is critical for promoting multidisciplinary research in nanotechnology, ML, and healthcare. These collaborations, by exploiting each sector's distinct strengths, have the potential to lead to major advances in medical diagnostics and treatment options, ultimately improving patient outcomes and boosting healthcare technology.

8. Recommendations

To fully realize the potential of ML and nanotechnology in precision medicine, a comprehensive strategy that considers funding, ethical considerations, cooperative research, and regulatory developments is needed. Prioritizing interdisciplinary collaborations among biomedical researchers, physicians, AI experts, and nanotechnologists could accelerate the conversion of discoveries into practical applications. Improved public and private sector funding is needed to support innovation, especially in fields such as AI-driven drug discovery, personalized therapeutics, regenerative medicine, and predictive diagnostics. International research networks will facilitate data sharing, standardization of AI models, and incorporation of nanomedicine into traditional medical treatments.

Establishing a robust ethical and regulatory framework is necessary to ensure patient safety, data privacy, and equitable access to state-of-the-art medical technology. Regulatory bodies must work to provide more accurate guidelines for AI-driven nanomedicine while ensuring accelerated clearance procedures for nanotechnology-based treatments. Strong cybersecurity and encryption methods are crucial to avoid unauthorized access to genetic and biometric data due to the complexity of patient data in precision medicine. Bias in AI models must also be addressed to ensure that precision medicine serves all populations, regardless of socioeconomic status or geographic location, and to eliminate global health disparities. To lower production costs and improve accessibility, more nanotechnology-based medical gadgets should be manufactured. Widespread clinical application will be made possible by improvements in the efficiency of drug delivery and imaging devices, brought about by advancements in nanomaterial fabrication and AI-driven optimization. To ensure that these cutting-edge technologies do not remain exclusive to high-income countries, special attention should be paid to the application of nanotech-ML solutions in low-resource situations.

Furthermore, by establishing a fully AI-integrated environment in which personalized therapy is powered by autonomous diagnostics, real-time therapeutic adjustments, and predictive analytics, nanotechnology and ML have the potential to transform healthcare delivery. Advances in quantum computing will accelerate AI-driven drug development by enabling the precise and rapid identification of therapeutic targets. The application of artificial intelligence and nanotechnology in gene editing and regenerative medicine could significantly expand the range of treatments available for genetic abnormalities, cancer, and neurological conditions. To achieve this, governments, academic institutions, and IT executives must collaborate to create an environment that promotes innovation while reducing obstacles related to cost, technology, and ethics. Through wise investments, interdisciplinary collaborations, and appropriate AI governance, nanotechnology and ML will not only redefine modern medicine but also establish a new standard for patient-centered and precision-driven healthcare worldwide.

9. Conclusion

This article highlights the combined potential of nanotechnology and ML to revolutionize precision medicine. By pairing molecular-scale nanoparticles with data-driven algorithms, healthcare can shift from reactive treatment to personalized preventive care. Smart nanocarriers deliver diagnostics and therapeutics to previously inaccessible targets, whereas ML models rapidly decode complex biological signals and guide clinical decisions in real time. Continued progress in biodegradable materials, AI-directed drug discovery, adaptive nanosystems, and multi-omics analytics will accelerate the development of closed-loop medical solutions. To translate these innovations into routine practice, stakeholders must prioritize transparent data governance, reproducible manufacturing, patient-centered ethics, and financing models that keep advanced care affordable and accessible globally.

CRediT authorship contribution statement

Shuaibu Saidu Musa: Writing – review & editing, Writing – original draft, Conceptualization. **Adamu Muhammad Ibrahim:** Writing – review & editing, Writing – original draft. **Muhammad Yasir Alhassan:** Writing – review & editing, Writing – original draft. **Abubakar Hafs Musa:** Writing – review & editing, Writing – original draft, Conceptualization. **Abdulrahman Garba Jibo:** Writing – review & editing, Writing – original draft. **Auwal Rabiu Auwal:** Writing – review & editing, Writing – original draft. **Olalekan John Okesanya:** Writing – review & editing, Writing – original draft. **Zhinya Kawa Othman:** Writing – review & editing, Writing – original draft. **Muhammad Sadiq Abubakar:** Writing – review & editing, Writing – original draft. **Mohamed Mustaf Ahmed:** Writing – review & editing, Writing – original draft. **Carina Joane V. Barroso:** Writing – review & editing, Writing – original draft. **Abraham Fessehaye Sium:** Writing – review & editing, Writing – original draft. **Manuel B. Garcia:** Writing – review & editing, Writing – original draft. **James Brian Flores:** Writing – review & editing, Writing – original draft. **Adamu Safiyanu Maikifi:** Writing – review & editing, Writing – original draft. **M.B.N. Kouwenhoven:** Writing – review & editing, Writing – original draft. **Don Eliseo Lucero-Prisno:** Supervision.

Ethical consideration

Not required.

Ethics statement

This manuscript is a narrative literature review and does not involve human or animal participants. Therefore, ethical approval was not required.

Funding

This article did not receive any funding from any governmental, commercial, or non-profit organisation.

Declaration of competing interest

All authors declare that there is no conflict of interest with respect to this manuscript.

References

[1] Ashley EA. Towards precision medicine. Nat Rev Genet 2016;17:507–22.
[2] Health C for D and R. Precision medicine [Internet]. FDA. FDA; 2023. Available from: https://www.fda.gov/medical-devices/in-vitro-diagnostics/precision-medicine. [Accessed 17 March 2025].
[3] Duffy DJ. Problems, challenges and promises: perspectives on precision medicine. Brief Bioinform 2016;17:494–504.
[4] Abbaoui W, Retal S, El Bhiri B, Kharmoum N, Ziti S. Towards revolutionizing precision healthcare: a systematic literature review of artificial intelligence methods in precision medicine. Inform Med Unlocked 2024;46:101475.
[5] Nanomedicine. Definition, research, & applications. Britannica; 2025. Available from: https://www.britannica.com/science/nanomedicine. [Accessed 17 March 2025].
[6] Anuyah S, Singh MK, Nyavor H. Advancing clinical trial outcomes using deep learning and predictive modelling: bridging precision medicine and patient-centered care. World J Adv Res Rev 2024;24:1–25.
[7] Alghamdi MA, Fallica AN, Virzì N, Kesharwani P, Pittalà V, Greish K. The promise of nanotechnology in personalized medicine. J Pers Med 2022;12:673.
[8] Delpierre C, Lefèvre T. Precision and personalized medicine: what their current definition says and silences about the model of health they promote. Implication for the development of personalized health. Front Sociol [Internet] 2023;8. Available from: https://www.frontiersin.org/journals/sociology/articles/10.3389/fsoc.2023.1112159/full. [Accessed 17 March 2025].
[9] Ginsburg GS, Phillips KA. Precision medicine: from science to value. Health Aff (Millwood) 2018;37:694–701.
[10] Nilius H, Tsouka S, Nagler M, Masoodi M. Machine learning applications in precision medicine: overcoming challenges and unlocking potential. TrAC Trends Anal Chem. 2024;179:117872.
[11] Shivahare BD, Singh J, Ravi V, Chandan RR, Alahmadi TJ, Singh P, et al. Delving into machine learning's influence on disease diagnosis and prediction. Available from: https://openpublichealthjournal.com/VOLUME/17/ELOCATOR/e18749445297804/FULLTEXT/. [Accessed 3 May 2025].
[12] Swain KP, Samal SR, Ravi V, Nayak SR, Alahmadi TJ, Singh P, et al. Towards early intervention: detecting Parkinson's disease through voice analysis with machine learning. Available from: https://openbiomedicalengineeringjournal.com/VOLUME/18/ELOCATOR/e18741207294056/ABSTRACT/. [Accessed 3 May 2025].
[13] Diwakar M, Tripathi A, Joshi K, Memoria M, Singh P, kumar N. Latest trends on heart disease prediction using machine learning and image fusion. Mater Today Proc 2021;37:3213–8.
[14] Ghorbian M, Ghobaei-Arani M, Babaei MR, Ghorbian S. Nanotechnology and nanosensors in personalized healthcare: a comprehensive review. Sens Biosens Res 2025;47:100740.
[15] Feng Z, Fan H, Cheng L, Zhang H, Fan H, Liu J. Advanced biomimetic nanomaterials for non-invasive disease diagnosis. Front Mater [Internet] 2021;8. Available from: https://www.frontiersin.orghttps://www.frontiersin.org/journals/materials/articles/10.3389/fmats.2021.664795/full. [Accessed 3 May 2025].
[16] Paluszkiewicz P, Martuszewski A, Zaręba N, Wala K, Banasik M, Kepinska M. The application of nanoparticles in diagnosis and treatment of kidney diseases. Int J Mol Sci 2022;23:131.
[17] Ioannou P, Baliou S, Samonis G. Nanotechnology in the diagnosis and treatment of antibiotic-resistant infections. Antibiotics 2024;13:121.
[18] Lan H, Jamil M, Ke G, Dong N. The role of nanoparticles and nanomaterials in cancer diagnosis and treatment: a comprehensive review. Am J Cancer Res 2023;13:5751–84.
[19] Adir O, Poley M, Chen G, Froim S, Krinsky N, Shklover J, et al. Integrating artificial intelligence and nanotechnology for precision cancer medicine. Adv Mater. 2020;32:1901989.
[20] Zhang Y, Yang H, Yu Y, Zhang Y. Application of nanomaterials in proteomics-driven precision medicine. Theranostics 2022;12:2674–86.
[21] Ashreetha B, Sumanth U, Kumar Reddy LN, Prasad K, Venkata Srinivas KN, V DG. Precision medicine in oncology - leveraging machine learning for accurate neoplasm diagnosis. In: 2024 5th int conf emerg technol INCET [internet]; 2024.

p. 1–7. https://ieeexplore.ieee.org/document/10593499. [Accessed 17 March 2025].
[22] Mao L, Wang L, Hu LS, Eschbacher JM, Leon GD, Singleton KW, et al. Weakly-supervised transfer learning with application in precision medicine. IEEE Trans Autom Sci Eng 2024;21:6250–64.
[23] Arora S, Nimma D, Kalidindi N, Asha SMR, Eluri NR, Florence MMV. Integrating machine learning with nanotechnology for enhanced cancer detection and treatment. South East Eur J Public Health 2024:748–55.
[24] Sim S, Wong NK. Nanotechnology and its use in imaging and drug delivery (Review). Biomed Rep 2021;14(5):42. https://doi.org/10.3892/br.2021.1418.
[25] Gu W, Meng F, Haag R, Zhong Z. Actively targeted nanomedicines for precision cancer therapy: concept, construction, challenges and clinical translation. J Controlled Release 2021;329:676–95.
[26] Mitchell MJ, Billingsley MM, Haley RM, Wechsler ME, Peppas NA, Langer R. Engineering precision nanoparticles for drug delivery. Nat Rev Drug Discov 2021; 20:101–24.
[27] Hristova-Panusheva K, Xenodochidis C, Georgieva M, Krasteva N. Nanoparticle-mediated drug delivery systems for precision targeting in oncology. Pharmaceuticals 2024;17:677.
[28] Pathade AD, Kommineni N, Bulbake U, Thummar MM, Samanthula G, Khan W. Preparation and comparison of oral bioavailability for different nano-formulations of olaparib. AAPS PharmSciTech 2019;20:276.
[29] Aljabali AAA, Obeid MA, Gammoh O, El-Tanani M, Mishra V, Mishra Y, et al. Nanomaterial-driven precision immunomodulation: a new paradigm in therapeutic interventions. Cancers 2024;16:2030.
[30] Visan AI, Negut I. Integrating artificial intelligence for drug discovery in the context of revolutionizing drug delivery. Life 2024;14:233.
[31] Agboklu M, Adrah FA, Agbenyo PM, Nyavor H. From bits to atoms: machine learning and nanotechnology for cancer therapy. J Nanotechnol Res. 2024;6: 16–26.
[32] Zhan Y, Hao Y, Wang X, Guo D. Advances of artificial intelligence in clinical application and scientific research of neuro-oncology: current knowledge and future perspectives. Crit Rev Oncol Hematol 2025;209:104682.
[33] Shi X, Wang X, Yao W, Shi D, Shao X, Lu Z, et al. Mechanism insights and therapeutic intervention of tumor metastasis: latest developments and perspectives. Signal Transduct Target Ther 2024;9:192.
[34] Taha BA, Ahmed NM, Talreja RK, Haider AJ, Mashhadany YA, Al-Jubouri Q, et al. Synergizing nanomaterials and artificial intelligence in advanced optical biosensors for precision antimicrobial resistance diagnosis. ACS Synth Biol [Internet] 2024. Available from: https://pubs.acs.org/doi/abs/10.1021/acssynbio.4c00070. [Accessed 3 May 2025].
[35] Chen J, Fu S, Zhang C, Liu H, Su X. DNA logic circuits for cancer theranostics. Small 2022;18:2108008.
[36] Guo J, Pan X, Wang C, Liu H. Molecular imaging-guided sonodynamic therapy. Bioconjug Chem. 2022;33:993–1010.
[37] Helsper S, Yuan X, Bagdasarian FA, Athey J, Li Y, Borlongan CV, et al. Multinuclear MRI reveals early efficacy of stem cell therapy in stroke. Transl Stroke Res 2023;14:545–61.
[38] Colbaugh R, Glass K, Global V. Detecting and monitoring brain disorders using smartphones and machine learning [internet]. medRxiv 2020. p. 2020.10.03.20206235. Available from: https://www.medrxiv.org/content/10.1101/2020.10.03.20206235v1. [Accessed 18 March 2025].
[39] McEvoy AC, Warburton L, Al-Ogaili Z, Celliers L, Calapre L, Pereira MR, et al. Correlation between circulating tumour DNA and metabolic tumour burden in metastatic melanoma patients. BMC Cancer 2018;18:726.
[40] Marsavela G, McEvoy AC, Pereira MR, Reid AL, Al-Ogaili Z, Warburton L, et al. Detection of clinical progression through plasma ctDNA in metastatic melanoma patients: a comparison to radiological progression. Br J Cancer 2022;126:401–8.
[41] Noorbakhsh-Sabet N, Zand R, Zhang Y, Abedi V. Artificial intelligence transforms the future of health care. Am J Med 2019;132:795–801.
[42] Johnson KB, Wei W-Q, Weeraratne D, Frisse ME, Misulis K, Rhee K, et al. Precision medicine, AI, and the future of personalized health care. Clin Transl Sci. 2021;14:86–93.
[43] Petersson L, Svedberg P, Nygren JM, Larsson I. Healthcare leaders' perceptions of the usefulness of AI applications in clinical work: a qualitative study. Caring shar – exploit value data health innov [Internet]. IOS Press; 2023. p. 678–9. https://ebooks.iospress.nl/doi/10.3233/SHTI230235. [Accessed 18 March 2025].
[44] Lee D, Yoon SN. Application of artificial intelligence-based technologies in the healthcare industry: opportunities and challenges. Int J Environ Res Public Health 2021;18:271.
[45] Lee J-T, Hsieh C-C, Lin C-H, Lin Y-J, Kao C-Y. Prediction of hospitalization using artificial intelligence for urgent patients in the emergency department. Sci Rep 2021;11:19472.
[46] Naik N, Hameed BMZ, Shetty DK, Swain D, Shah M, Paul R, et al. Legal and ethical consideration in artificial intelligence in healthcare: who takes responsibility? Front Surg [Internet] 2022;9. Available from: https://www.frontiersin.org/journals/surgery/articles/10.3389/fsurg.2022.862322/full. [Accessed 18 March 2025].
[47] Carey K, Ryu J, Uh K, Lengi AJ, Clark-Deener S, Corl BA, et al. Frequency of off-targeting in genome edited pigs produced via direct injection of the CRISPR/Cas9 system into developing embryos. BMC Biotechnol 2019;19:25.
[48] Akshaya N, A R, Abhishek H, Shramana B, Ashwin AB, Nidhal S. Anesthesiology's next frontier: exploring the boundless potential of artificial intelligence. Int J Pharm Chem Anal 2023;10:3–7.
[49] Rajkomar A, Oren E, Chen K, Dai AM, Hajaj N, Hardt M, et al. Scalable and accurate deep learning with electronic health records. npj Digit Med 2018;1: 1–10.
[50] Fatima I, Grover V, Khan IR, Ahmad N, Yadav A. Artificial intelligence in medical field. EAI Endorsed Trans Pervasive Health Technol [Internet] 2023;9. Available from: https://publications.eai.eu/index.php/phat/article/view/4713. [Accessed 18 March 2025].
[51] Rana MS, Shuford J. AI in healthcare: transforming patient care through predictive analytics and decision support systems. J Artif Intell Gen Sci JAIGS ISSN3006-4023 [Internet] 2024;1. Available from: https://ojs.boulibrary.com/index.php/JAIGS/article/view/30. [Accessed 18 March 2025].
[52] Ahmed A, Adil K. Transforming healthcare systems with artificial intelligence: revolutionizing efficiency, quality, and patient care [internet]. Research Square 2023. Available from: https://www.researchsquare.com/article/rs-3175341/v1. [Accessed 18 March 2025].
[53] Shajari S, Kuruvinashetti K, Komeili A, Sundararaj U. The emergence of AI-based wearable sensors for digital health technology: a review. Sensors (Peterb, NH) 2023;23:9498.
[54] Li Y, Chen B, Yang S, Jiao Z, Zhang M, Yang Y, et al. Advances in environmental pollutant detection techniques: enhancing public health monitoring and risk assessment. Environ Int 2025;197:109365.
[55] Kuznetsova V, Coogan Á, Botov D, Gromova Y, Ushakova EV, Gun'ko YK. Expanding the horizons of machine learning in nanomaterials to chiral nanostructures. Adv Mater Deerfield Beach Fla 2024;36:e2308912.
[56] Gupta SL, Basu S. Smart nanosensors in healthcare recent developments and applications. Nanosensors futur smart intell healthc syst. CRC Press; 2022.
[57] Saylan Y, Akgönüllü S, Denizli A. Chapter 9 - nanosensors for medical diagnosis. In: Denizli A, Nguyen TA, Rajan M, Alam MF, Rahman K, editors. Nanotechnol hematol blood transfus artif blood [Internet]. Elsevier; 2022. p. 195–213. https://www.sciencedirect.com/science/article/pii/B9780128239711000167. [Accessed 4 May 2025].
[58] Kim S-J, Choi S-J, Jang J-S, Cho H-J, Kim I-D. Innovative nanosensor for disease diagnosis. Acc Chem Res 2017;50:1587–96.
[59] Yang J, Carey P, Ren F, Lobo BC, Gebhard M, Leon ME, et al. Chapter 24 - nanosensor networks for health-care applications. In: Han B, Tomer VK, Nguyen TA, Farmani A, Kumar Singh P, editors. Nanosensors smart cities [Internet]. Elsevier; 2020. p. 405–17. https://www.sciencedirect.com/science/article/pii/B9780128198704000232. [Accessed 4 May 2025].
[60] Palaniyandi T, B K, Prabhakaran P, Viswanathan S, Rahaman Abdul Wahab M, Natarajan S, et al. Nanosensors for the diagnosis and therapy of neurodegenerative disorders and inflammatory bowel disease. Acta Histochem 2023;125:151997.
[61] Rabbani M, Hoque ME, Mahbub ZB. Chapter 7 - nanosensors in biomedical and environmental applications: perspectives and prospects. In: Pal K, Gomes F, editors. Nanofabrication smart nanosensor appl [Internet]. Elsevier; 2020. p. 163–86. https://www.sciencedirect.com/science/article/pii/B9780128207024000076. [Accessed 4 May 2025].
[62] Mujawar MA, Gohel H, Bhardwaj SK, Srinivasan S, Hickman N, Kaushik A. Nano-enabled biosensing systems for intelligent healthcare: towards COVID-19 management. Mater Today Chem 2020;17:100306.
[63] Noah NM, Ndangili PM. Nanosensor arrays: innovative approaches for medical diagnosis. Nanosensors futur smart intell healthc syst. CRC Press; 2022.
[64] Yaari Z, Yang Y, Apfelbaum E, Cupo C, Settle AH, Cullen Q, et al. A perception-based nanosensor platform to detect cancer biomarkers. Sci Adv 2021;7: eabj0852.
[65] Peng G, Hakim M, Broza YY, Billan S, Abdah-Bortnyak R, Kuten A, et al. Detection of lung, breast, colorectal, and prostate cancers from exhaled breath using a single array of nanosensors. Br J Cancer 2010;103:542–51.
[66] Madhugiri VS, Prasad D. Early experience with an artificial intelligence-based module for brain metastasis detection and segmentation. J Neuro Oncol 2025; 171:365–72.
[67] Huang Y, Bert C, Sommer P, Frey B, Gaipl U, Distel LV, et al. Deep learning for brain metastasis detection and segmentation in longitudinal MRI data. Med Phys 2022;49:5773–86.
[68] Dong H, Lin J, Tao Y, Jia Y, Sun L, Li WJ, et al. AI-enhanced biomedical micro/nanorobots in microfluidics. Lab Chip 2024;24:1419–40.
[69] Wang G, Qiu M, Xing X, Zhou J, Yao H, Li M, et al. Lung cancer scRNA-seq and lipidomics reveal aberrant lipid metabolism for early-stage diagnosis. Sci Transl Med 2022;14:eabk2756.
[70] Hollon T, Jiang C, Chowdury A, Nasir-Moin M, Kondepudi A, Aabedi A, et al. Artificial-intelligence-based molecular classification of diffuse gliomas using rapid, label-free optical imaging. Nat Med 2023;29:828–32.
[71] Malik S, Muhammad K, Waheed Y. Emerging applications of nanotechnology in healthcare and medicine. Molecules (Basel) 2023;28:6624.
[72] Tsvetkov PO, Eyraud R, Ayache S, Bougaev AA, Malesinski S, Benazha H, et al. An AI-powered blood test to detect cancer using NanoDSF. Cancers. 2021;13:1294.
[73] Podnar S, Kukar M, Gunčar G, Notar M, Gošnjak N, Notar M. Diagnosing brain tumours by routine blood tests using machine learning. Sci Rep 2019;9:14481.
[74] Ho D, Quake SR, McCabe ERB, Chng WJ, Chow EK, Ding X, et al. Enabling technologies for personalized and precision medicine. Trends Biotechnol 2020; 38:497–518.
[75] Tomar A, Gupta N. Prediction for the spread of COVID-19 in India and effectiveness of preventive measures. Sci Total Environ 2020;728:138762.
[76] Tiwari S, Kumar S, Guleria K. Outbreak trends of coronavirus disease-2019 in India: a prediction. Disaster Med Public Health Prep 2020;14:e33–8.

[77] Oh Y, Park S, Ye JC. Deep learning COVID-19 features on CXR using limited training data sets. IEEE Trans Med Imaging 2020;39:2688–700.
[78] The role of imaging in the detection and management of COVID-19: a review [internet]. Available from: https://ieeexplore.ieee.org/document/9079648. [Accessed 4 May 2025].
[79] Naaz S, Asghar A. Artificial intelligence, nano-technology and genomic medicine: the future of anaesthesia. J Anaesthesiol Clin Pharmacol 2022;38:11.
[80] Tripathy A, Patne AY, Mohapatra S, Mohapatra SS. Convergence of nanotechnology and machine learning: the state of the art, challenges, and perspectives. Int J Mol Sci 2024;25:12368.
[81] Mogami R, Lopes AJ, Araújo Filho RC, de Almeida FCS, Messeder AM da C, Koifman ACB, et al. Chest computed tomography in COVID-19 pneumonia: a retrospective study of 155 patients at a university hospital in Rio de Janeiro, Brazil. Radiol Bras 2021;54:1–8.
[82] Kumar S, Kumar H, Kumar G, Singh SP, Bijalwan A, Diwakar M. A methodical exploration of imaging modalities from dataset to detection through machine learning paradigms in prominent lung disease diagnosis: a review. BMC Med Imaging 2024;24:30.
[83] Armato SG, Hadjiiski L, Tourassi GD, Drukker K, Giger ML, Li F, et al. LUNGx Challenge for computerized lung nodule classification: reflections and lessons learned. J Med Imaging 2015;2:020103.
[84] COVID-19-NY-SBU [Internet]. Cancer Imaging Arch. TCIA. [cited 2025 May 4]. Available from: https://www.cancerimagingarchive.net/collection/covid-19-ny-sbu/.
[85] CT-IMAGES-IN-COVID-19 [Internet]. Cancer Imaging Arch. TCIA. [cited 2025 May 4]. Available from: https://www.cancerimagingarchive.net/collection/ct-images-in-covid-19/.
[86] Wang L, Lin ZQ, Wong A. COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images. Sci Rep 2020;10:19549.
[87] G C. Detection of Covid-19 and other pneumonia cases from CT and X-ray chest images using deep learning based on feature reuse residual block and depthwise dilated convolutions neural network. Appl Soft Comput [Internet] 2023;133. Available from: https://pubmed.ncbi.nlm.nih.gov/36504726/. [Accessed 4 May 2025].
[88] Rk S, R P, Rn B. COVIDScreen: explainable deep learning framework for differential diagnosis of COVID-19 using chest X-rays. Neural Comput Appl [Internet] 2021;33. Available from: https://pubmed.ncbi.nlm.nih.gov/33437132/. [Accessed 4 May 2025].
[89] Keles A, Keles MB, Keles A. COV19-CNNet and COV19-ResNet: diagnostic inference engines for early detection of COVID-19. Cogn Comput 2024;16:1612–22.
[90] Kong X, Gao P, Wang J, Fang Y, Hwang KC. Advances of medical nanorobots for future cancer treatments. J Hematol OncolJ Hematol Oncol 2023;16:74.
[91] Olawade DB, Ige AO, Olaremu AG, Ijiwade JO, Adeola AO. The synergy of artificial intelligence and nanotechnology towards advancing innovation and sustainability - a mini-review. Nano Trends 2024;8:100052.
[92] Zhang X, Li W, Chen X, Lu S. MoodExplorer: towards compound emotion detection via smartphone sensing. Proc ACM Interact Mob Wearable Ubiquitous Technol 2018;1:176:1–176:30.
[93] Sharma T, Diwakar M, Singh P, Lamba S, Kumar P, Joshi K. Emotion Analysis for predicting the emotion labels using Machine Learning approaches. In: 2021 IEEE 8th Uttar Pradesh sect int conf electr electron comput eng UPCON [Internet]; 2021. p. 1–6. https://ieeexplore.ieee.org/document/9667562. [Accessed 4 May 2025].
[94] Batbaatar E, Li M, Ryu KH. Semantic-emotion neural network for emotion recognition from text. IEEE Access 2019;7:111866–78.
[95] Seyeditabari A, Tabari N, Gholizadeh S, Zadrozny W. Emotion detection in text: focusing on latent representation [Internet]. arXiv 2019. Available from: http://arxiv.org/abs/1907.09369. [Accessed 4 May 2025].
[96] Hamid A, Ali KB. A machine learning based analysis of heart disease diagnosis. In: 2023 int conf integr comput intell syst ICICIS [Internet]; 2023. p. 1–5. https://ieeexplore.ieee.org/document/10430309. [Accessed 4 May 2025].
[97] Acharya D, Mukhopadhyay A. A comprehensive review of machine learning techniques for multi-omics data integration: challenges and applications in precision oncology. Brief Funct Genomics 2024;23:549–60.
[98] Leong YX, Tan EX, Leong SX, Lin Koh CS, Thanh Nguyen LB, Ting Chen JR, et al. Where nanosensors meet machine learning: prospects and challenges in detecting disease X. ACS Nano 2022;16:13279–93.
[99] Douard N, LaRovere J, Parmar V, Straulino D, Harris MD, McCann C, et al. Multimodal machine learning for multifactor geospatial prioritization of suitable healthcare facility sites. In: 2024 IEEE int conf imaging syst tech IST [Internet]; 2024. p. 1–5. Available from: https://ieeexplore.ieee.org/document/10759173. [Accessed 18 March 2025].
[100] Agrahari V, Agrahari V, Chou M-L, Chew CH, Noll J, Burnouf T. Intelligent micro-/nanorobots as drug and cell carrier devices for biomedical therapeutic advancement: promising development opportunities and translational challenges. Biomaterials 2020;260:120163.
[101] Advancing precision medicine: emerging trends and technologies [internet]. Sengenics; 2024. Available from: https://sengenics.com/blog/advancing-precision-medicine-emerging-trends-technologies/. [Accessed 18 March 2025].
[102] Alvarez MM, Aizenberg J, Analoui M, Andrews AM, Bisker G, Boyden ES, et al. Emerging trends in micro- and nanoscale technologies in medicine: from basic discoveries to translation. ACS Nano 2017;11:5195–214.
[103] Seyhan AA, Carini C. Are innovation and new technologies in precision medicine paving a new era in patients centric care? J Transl Med 2019;17:114.
[104] Wang Y, Jin X, Castro C. Accelerating the characterization of dynamic DNA origami devices with deep neural networks. Sci Rep 2023;13:15196.
[105] Kasture K, Shende P. Amalgamation of artificial intelligence with nanoscience for biomedical applications. Arch Comput Methods Eng 2023;30:4667–85.
[106] Jiang Z, Xu FF, Gao L, Sun Z, Liu Q, Dwivedi-Yu J, et al. Active retrieval augmented generation [Internet]. arXiv 2023. Available from: http://arxiv.org/abs/2305.06983. [Accessed 29 May 2025].
[107] Salemi A, Zamani H. Evaluating retrieval quality in retrieval-augmented generation [Internet]. arXiv 2024. Available from: http://arxiv.org/abs/2404.13781. [Accessed 29 May 2025].
[108] Khan A, AlBarri S, Manzoor MA. Contrastive self-supervised learning: a survey on different architectures. In: 2022 2nd int conf artif Intell ICAI [Internet]; 2022. p. 1–6. https://ieeexplore.ieee.org/document/9773725. [Accessed 29 May 2025].
[109] Li K, Wang L, Liu L, Ran Q, Xu K, Guo Y. Decoupling makes weakly supervised local feature better. In: 2022 IEEECVF conf comput vis pattern recognit CVPR [Internet]; 2022. p. 15817–27. https://ieeexplore.ieee.org/document/9880047. [Accessed 29 May 2025].
[110] Aldoseri A, Al-Khalifa KN, Hamouda AM. Re-thinking data strategy and integration for artificial intelligence: concepts, opportunities, and challenges. Appl Sci 2023;13:7082.
[111] Kumar S, Rani S, Sharma S, Min H. Multimodality fusion aspects of medical diagnosis: a comprehensive review. Bioeng Basel Switz. 2024;11:1233.
[112] Haick H, Tang N. Artificial intelligence in medical sensors for clinical decisions. ACS Nano 2021;15:3557–67.
[113] Bi Y, Xie S, Li Z, Dong S, Teng L. Precise nanoscale fabrication technologies, the “last mile” of medicinal development. Acta Pharm Sin B [Internet] 2025. Available from: https://www.sciencedirect.com/science/article/pii/S2211383525001807. [Accessed 4 May 2025].
[114] Bhange M, Telange D. Convergence of nanotechnology and artificial intelligence in the fight against liver cancer: a comprehensive review. Discov Oncol 2025;16:77.
[115] Jena GK, Patra CN, Jammula S, Rana R, Chand S. Artificial intelligence and machine learning implemented drug delivery systems: a paradigm shift in the pharmaceutical industry. J Bio-X Res 2024;7:16.
[116] Letoffe O, Huang X, Asher N, Marques-Silva J. From SHAP scores to feature importance scores [internet]. arXiv 2024. Available from: http://arxiv.org/abs/2405.11766. [Accessed 29 May 2025].
[117] Takefuji Y. Beyond XGBoost and SHAP: unveiling true feature importance. J Hazard Mater 2025;488:137382.
[118] Neal Joshua ES, Bhattacharyya D, Chakkravarthy M, Byun Y-C. 3D CNN with visual insights for early detection of lung cancer using gradient-weighted class activation. J Healthc Eng 2021;2021:6695518.
[119] Hussain T, Shouno H. Explainable deep learning approach for multi-class brain magnetic resonance imaging tumor classification and localization using gradient-weighted class activation mapping. Information (Basel) 2023;14:642.
[120] Henry A-I, Sharma B, Cardinal MF, Kurouski D, Van Duyne RP. Surface-enhanced Raman spectroscopy biosensing: in vivo diagnostics and multimodal imaging. Anal Chem. 2016;88:6638–47.
[121] Wu W, Ranasinghe JC, Chatterjee A, Huang S. Recent advances on Raman spectroscopy of graphene: towards biosensing applications. Mater Chem Phys 2024;318:129281.
[122] Jaber HAH, Saleh Z, Jaber W, Badran A, Nasser H, Jaber HAH, et al. Artificial Intelligence Integration With Nanotechnology [Internet]. Httpsservicesigi-Glob.-8-3693-0368-9ch002. IGI Global Scientific Publishing; 1AD. [cited 2025 Mar 18]. Available from: https://www.igi-global.com/gateway/chapter/www.igi-global.com/gateway/chapter/334932.
[123] Hulsen T, Jamuar SS, Moody AR, Karnes JH, Varga O, Hedensted S, et al. From big data to precision medicine. Front Med [Internet] 2019;6. Available from: https://www.frontiersin.org/journals/medicine/articles/10.3389/fmed.2019.00034/full. [Accessed 18 March 2025].
[124] Gupta NS, Kumar P. Perspective of artificial intelligence in healthcare data management: a journey towards precision medicine. Comput Biol Med 2023;162:107051.
[125] Azencott C-A. Machine learning and genomics: precision medicine versus patient privacy. Philos Trans R Soc Math Phys Eng Sci. 2018;376:20170350.
[126] Jaber HM, Saleh ZA, Jaber W, Amil W, Jaber HM, Saleh ZA, et al. Ethical and Social Implications of AI and Nanotechnology [Internet]. Httpsservicesigi-Glob.-8-3693-0368-9ch010. IGI Global Scientific Publishing; 1AD. [cited 2025 Mar 18]. Available from: https://www.igi-global.com/gateway/chapter/www.igi-global.com/gateway/chapter/334940.
[127] Nanorevolution in medicine: synergy of nanotechnology, artificial intelligence and digital innovation [Internet]. Med Sestra 2024. Available from: https://medsestrajournal.ru/en/25879979-2024-07-06. [Accessed 18 March 2025].
[128] Jonsson JJ, Stefansdottir V. Ethical issues in precision medicine. Ann Clin Biochem 2019;56:628–9.
[129] Ahmed Z, Mohamed K, Zeeshan S, Dong X. Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine. [cited 2025 March 18]; Available from: https://dx.doi.org/10.1093/database/baaa010.
[130] Martínez-García M, Hernández-Lemus E. Data integration challenges for machine learning in precision medicine. Front Med [Internet] 2022;8. Available from: https://www.frontiersin.org/journals/medicine/articles/10.3389/fmed.2021.784455/full. [Accessed 18 March 2025].
[131] R. B, M. P, M. D, M. S, Natarajan AK, R. B, et al. Advancing Precision Medicine: Integrating AI and Machine Learning for Personalized Healthcare Solutions

[Internet]. Httpsservicesigi-Glob.-8-3693-7462-7ch015. IGI Global Scientific Publishing; 1AD [cited 2025 Mar 18]. Available from: https://www.igi-global.com/gateway/chapter/www.igi-global.com/gateway/chapter/351612.
[132] Ijiga AC, Igbede MA, Ukaegbu C, Olatunde TI, Olajide FI, Enyejo LA, et al. Precision healthcare analytics: integrating ML for automated image interpretation, disease detection, and prognosis prediction. World J Biol Pharm Health Sci. 2024;18:336–54.
[133] Kurul F, Turkmen H, Cetin AE, Topkaya SN. Nanomedicine: how nanomaterials are transforming drug delivery, bio-imaging, and diagnosis. Nanotechnol 2025;7:100129.
[134] Sandoval B, MacDonald. Perspectives on FDA's regulation of nanotechnology: emerging challenges and potential solutions. Compr Rev Food Sci Food Saf 2009;8:375–93.
[135] Ahmed R, Maurya V, Dwivedi A, Mishra MK. Regulation of nanomaterials and nanomedicines for clinical application. https://www.eurekaselect.com/article/138951.
[136] Moisa SM, Burlacu A, Butnariu LI, Vasile CM, Brinza C, Spoiala EL, et al. Nanotechnology innovations in pediatric cardiology and cardiovascular medicine: a comprehensive review. Biomedicines 2024;12:185.
[137] Petzschner FH. Practical challenges for precision medicine. Science. 2024;383:149–50.
[138] Cross JL, Choma MA, Onofrey JA. Bias in medical AI: implications for clinical decision-making. PLOS Digit Health 2024;3:e0000651.
[139] Nazir S. Nanotechnology enhancing AI technology: a synergistic convergence for future innovation. Evol Mech Eng. 2023;5:1–2.
[140] Cai Z, Poulos RC, Liu J, Zhong Q. Machine learning for multi-omics data integration in cancer. iScience 2022;25:103798.
[141] Wekesa JS, Kimwele M. A review of multi-omics data integration through deep learning approaches for disease diagnosis, prognosis, and treatment. Front Genet [Internet] 2023;14. Available from: https://www.frontiersin.org/journals/genetics/articles/10.3389/fgene.2023.1199087/full. [Accessed 19 March 2025].
[142] Theodorakis N, Feretzakis G, Tzelves L, Paxinou E, Hitas C, Vamvakou G, et al. Integrating machine learning with multi-omics technologies in geroscience: towards personalized medicine. J Pers Med 2024;14:931.