



Integrating Artificial Intelligence and Nanotechnology to Advance Cancer Treatment

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Abstract

Cancer remains one of the leading causes of death worldwide, responsible for approximately 10 million deaths in 2020, or about one in six fatalities. The integration of artificial intelligence (AI) offers promising advancements in cancer diagnosis, enabling more accurate identification and classification of various cancer types. This progress is crucial for enhancing diagnostic precision for both doctors and patients.

Simultaneously, the field of nanomedicine is rapidly evolving, with versatile drug carriers being rigorously evaluated for their effectiveness in targeting tumor sites and improving localized drug delivery. Additionally, combining nano therapy with other treatment approaches is continually being assessed to boost therapeutic efficacy for cancer patients.

AI's role in cancer treatment extends beyond diagnosis. It significantly contributes to managing cancer by analyzing diverse datasets from various diagnostic methods, such as PSA levels, MRI-guided biopsies, genomic biomarkers, and Gleason grading. These methods help in diagnosing, stratifying risk, and monitoring patients, though they often involve a degree of subjectivity.

The synergy between AI and nanoparticles can mitigate subjectivity by revealing complex relationships and managing large datasets more effectively. AI algorithms, in conjunction with nanoparticle technology, promise to enhance diagnostic accuracy and overall efficiency, reducing resource use while improving outcomes.

This systematic review explores the latest advancements in nanoparticle-based neural networks and AI, focusing on their current roles in cancer diagnosis and management.

Keywords: cancer, Nanotechnology, artificial intelligence, nanoparticles, Targeted therapy

1. Introduction

Cancer is the leading cause of death worldwide, placing a significant burden on healthcare systems [1]. Despite its high mortality rate, substantial progress has been made in treating cancer over the past decades, with advancements such as targeted therapy, immunotherapy, and combination therapies [2,3].

In the last decade, nanomedicine has seen remarkable progress in diagnosing and managing diseases. The clinical application of nanomedicines has demonstrated their potential to enhance drug delivery through nanotechnology [4]. Artificial intelligence (AI) is poised to further revolutionize healthcare by leveraging large datasets to design precise nanomedicines for cancer management [5]. AI-driven advancements in nanotechnology can improve molecular and early diagnosis, fine-tune the properties of nanodrugs, achieve drug synergy, and minimize nanotoxicity. This leads to enhanced targetability, dose customization, and therapeutic efficacy.

The integration of AI and nanotechnology offers innovative solutions for treating various cancers. From advancing cancer diagnosis and identifying new drugs and targets to optimizing formulation designs and conducting clinical trials, AI has streamlined processes and reduced human workload, accelerating progress in the pharmaceutical industry [6]. Combining AI with nanoparticles (NPs) enhances material property optimization, targeted diagnosis and treatment, and interactions with biological systems.

This review explores the impact of artificial intelligence on the design and development of cancer drugs, focusing on the preparation and optimization of new nanotechnology-based drug formulations. It also addresses the prospects, challenges, and goals associated with implementing these emerging methods and technologies in intelligent cancer treatment.

2. Alternative chemotherapy

2.1. Problems of various types of cancer treatment

Conventional chemotherapy remains the most widely used cancer treatment, involving small, toxic molecules that target DNA to induce cell death [7]. However, these agents are non-selective and can harm healthy tissues, leading to significant side effects [8]. Additionally, cancers can develop resistance to traditional treatments, highlighting the need for ongoing research and the development of new therapies to address these challenges.

The primary objective of anticancer therapy is to specifically target malignant cells while sparing healthy ones. Traditional treatments, such as chemotherapy, radiotherapy, and surgery, often lead to severe side effects and considerable patient discomfort. Drug delivery systems designed for cancer targeting offer a promising alternative by providing selective targeting, improved efficacy, biocompatibility, and high drug loading [9]. Despite these advantages, technical, therapeutic, manufacturing, and clinical challenges currently limit their widespread use.

Nanoparticles (NPs) present opportunities for innovative cancer therapies but also pose potential risks [10]. Concerns about nanotechnology include public resistance, safety issues, and environmental impacts. Similarly, the integration of artificial intelligence (AI) into nanotechnology raises questions about its social

impact, ethical considerations, and potential job displacement. Nevertheless, nanotechnology has produced materials with remarkable properties, such as high strength and exceptional thermal and electrical conductivity. AI enhances the development of these materials by simulating their behavior under various conditions and guiding experimental efforts. Consequently, this combination of AI and nanotechnology promises to create advanced drugs with minimized side effects and improved therapeutic outcomes.

2.2. new strategies for increasing treatment efficiency

Recent advances in nanotechnology have enabled the development of nanoparticle (NP)-based drug formulations with superior properties compared to traditional small-molecule chemotherapy. These advancements include higher drug loading capacities, targeted delivery, and controlled or sustained release of anticancer agents [11]. Over the past 30 years, numerous nanomedicines have been designed and tested in laboratory animals for various tumor types [12]. However, only a few have successfully transitioned to clinical use and received approval from regulatory bodies such as the U.S. Food and Drug Administration (FDA) or the European Medicines Agency (EMA) [13]. This limited clinical translation remains a significant challenge for cancer nanomedicine.

In recent years, the rapid growth in computational power, the availability of extensive data, and the development of advanced data analysis algorithms have led to the emergence of machine learning (ML) and artificial intelligence (AI) methods. These technologies assist in predicting the absorption, distribution, metabolism, and excretion (ADME) properties, as well as the toxicity of chemicals and nanoparticles [14]. A summary of key methods highlights that artificial neural networks often outperform linear regression models. They efficiently process large datasets, handle incomplete data, manage both linear and nonlinear relationships, and uncover new insights beyond user inputs [15].

Enhanced quantitative models, particularly those based on DNA approaches, can significantly improve the design of cancer nanomedicines, leading to higher tumor delivery efficiency and better therapeutic outcomes.

3. Artificial intelligence adding cancer treatment

3.1. Artificial Intelligence (AI) contribution to cancer treatment

In recent years, artificial intelligence has captivated society's imagination, sparking widespread interest in its potential to enhance our lives [16]. AI is increasingly being utilized to improve disease diagnosis, management, and treatment development. As the number of cancer diagnoses rises and vast amounts of data are generated during treatment, there is a growing need for AI to advance oncological care [17]. Predictive AI in cancer treatment has the potential to significantly reduce mortality rates [18]. This section covers cancer diagnosis through deep learning methods, the use of medical imaging in cancer detection, mortality rates across various cancers, cancer-related datasets, and automated diagnostic techniques. Additionally, it explores the semi-automated approaches used in cancer detection.

3.2. AI in medical imaging

In clinical imaging, computer-aided detection (CADE) and computer-aided diagnosis (CADx) are system-based frameworks that assist healthcare professionals in making swift and accurate decisions [19]. Medical imaging processes and manages data that clinicians and specialists use to assess and investigate

abnormalities over time [9]. When enhanced with artificial intelligence techniques, clinical images can improve diagnostic accuracy at various stages of cancer development [20]. As such, clinical imaging is crucial for the early detection of malignancies, evaluation, and post-treatment monitoring [21]. (Figure.1) illustrates the different types of scans used in cancer diagnosis. Computed tomography (CT) helps doctors diagnose cancer and determine the size and shape of tumors. Nuclear medicine scans, such as bone scans, PET (positron emission tomography) scans, thyroid MUGA (multiple gated acquisition) scans, and gallium scans, are useful for identifying whether cancer has metastasized. Magnetic resonance imaging (MRI) aids specialists in detecting malignancies and assessing their spread within the body. X-rays also play a role in planning treatments, such as surgery or radiation therapy, while mammograms, a low-dose X-ray technique, are specifically used to detect breast cancer.

Cancer diagnosis typically involves radiological imaging to determine the extent of the disease and monitor improvements following treatment. The field of oncological imaging continues to expand, becoming more comprehensive and precise [22]. In line with this, Soubry et al. proposed an image-based computerized system for cancer immunotherapy [23]. Their approach enhances vaccine preparation through dendritic cell (DC) immunotherapy, incorporating various image-based algorithms with low computational time.

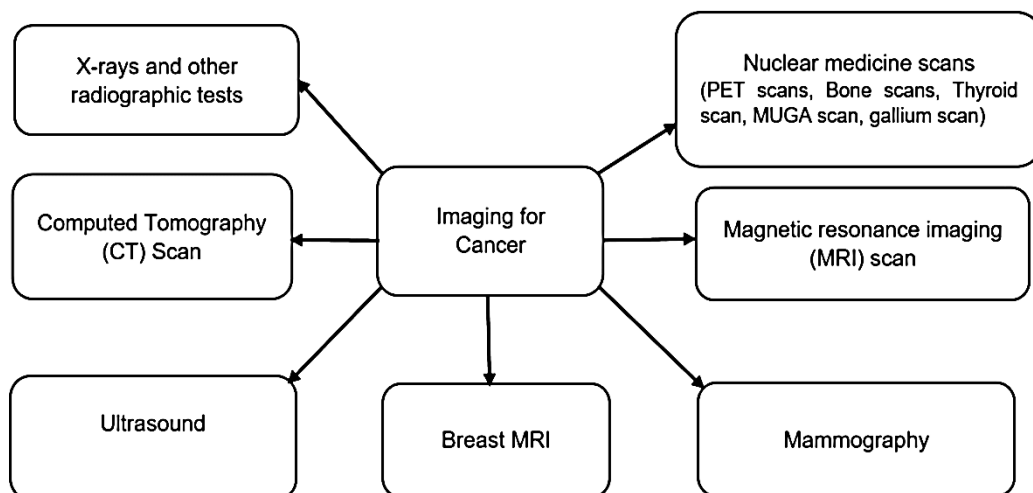


Fig.1 Types of cancer test imaging

3.3. Identification of new anticancer targets

Artificial intelligence (AI) has become a powerful tool in biological analysis, particularly in using genomic data to construct networks and identify co-expression modules of genes, proteins, metabolites, critical molecular pathways, and key molecules within these networks [24]. This study explores AI applications in biology from two main perspectives: network-based biological analysis and machine learning (ML)-based biological analysis. ML-based AI has been widely employed to identify new anticancer targets by analyzing large and complex biological data. These AI-driven programs can uncover potential reliable targets for effective treatments of human diseases by applying various methods, such as classification [26], clustering [27], and neural networks [28]. For instance, ML-based biological network analysis programs are designed to interrogate intricate datasets, leading to the identification of critical factors within classifications and specific biomarkers, such as gene or protein nodes, which are regarded as key targets [29]. Recent



advancements have seen the use of classification-based applications and molecular profiling techniques to improve the precision of cancer diagnosis and treatment. By analyzing genome-wide gene transcription profiles, protein expression profiles, and mutational landscapes, these AI-driven tools can more accurately classify tumor subtypes and identify specific biomarkers for targeted therapies [30]. This progress in AI and ML applications in biological analysis holds promise for developing more effective and personalized approaches to combating complex diseases like cancer.

3.4. AI and medical engineering

Artificial intelligence (AI) is revolutionizing the field of medicine and medical engineering, representing one of the most exciting new frontiers in healthcare. In recent years, AI has made significant progress in various aspects of medicine, from surgery to diagnostics [31]. One notable advancement is the use of robotic assistants in surgery, which has become increasingly common in specialized procedures. These robotic systems make surgeries less invasive and more precise, leading to improved patient outcomes. Additionally, AI plays a crucial role in gene sequencing and editing, enabling scientists to explore new treatment possibilities for a range of diseases [32]. Perhaps one of the most transformative impacts of AI in medical engineering is its potential to revolutionize disease diagnosis. In the near future, the way we diagnose and treat illnesses may differ significantly from today's methods. For example, imagine waking up with symptoms like fever and difficulty breathing. Typically, you would visit a doctor who would assess your condition and provide a diagnosis.

However, with AI's integration into medical practice, this process could look quite different. During a visit to the doctor, you might be asked about your symptoms, which would then be entered into sophisticated diagnostic software on a tablet—an application of AI in medical science and engineering. Within moments, the AI program could analyze your symptoms, cross-reference them with your entire medical history, and generate a list of potential diagnoses and treatment recommendations. The doctor could then review these AI-generated suggestions alongside their clinical evaluations to arrive at a more accurate diagnosis. AI's ability to process vast amounts of data and provide tailored insights is reshaping the landscape of medicine, paving the way for more precise, efficient, and personalized healthcare solutions.

4. Nanoparticles in medicine

4.1 Nanoparticles in cancer treatment

Polymeric nanocarriers have been extensively studied for the oral delivery of anticancer drugs due to their improved safety profiles. Polymers offer several advantages for drug delivery, including biocompatibility, biodegradability, and the versatility to bind with various molecules to form homo-block polymers. Additionally, polymers can be functionalized to target specific receptors, making them highly effective in delivering therapeutic agents [33]. The development of nanoparticles has revolutionized chemotherapy by providing a more targeted approach to drug delivery. As illustrated in (Figure.2), polymeric nanoparticles of specific sizes have a higher tendency to accumulate at tumor sites while sparing normal tissues from adverse effects [34]. This targeted drug release using nanocarriers allows for a more controlled and sustained release process, increasing drug concentration around the cancerous mass and minimizing damage to healthy cells. Polymeric carriers have garnered significant attention over the past few decades due to their multifunctionality and ability to be easily functionalized [35]. Generally, polymeric nanoparticles are small-sized colloidal solid systems where the drug can be physically dispersed, dissolved, or chemically attached to the polymer's main chain. One key benefit of using polymeric nanoparticles as drug carriers is

their ability to enhance the solubility and stability of drugs. This makes them one of the most widely used systems for drug delivery. Various polymers have been explored based on their distinct properties to optimize drug delivery effectiveness.

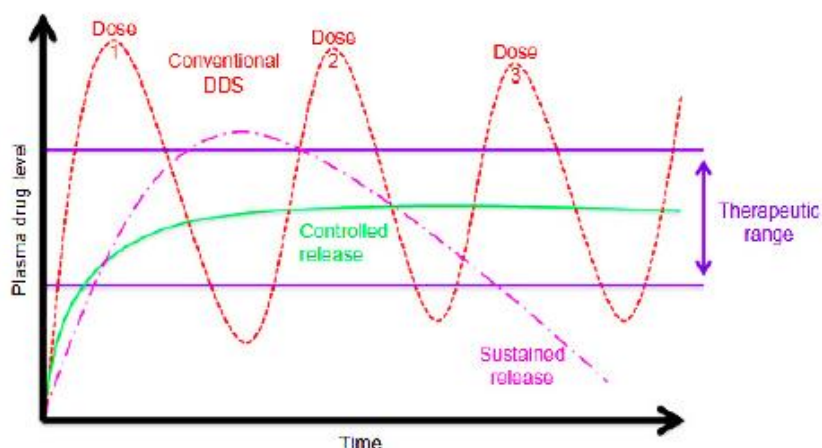


Fig.2 Change of drug concentration relative to the time of systemic method (red) drug release (green)

5. Combination of nanoparticles and artificial intelligence

5.1. The application of AI in the interpretation of molecular profiles identified by nanotechnology

Given the heterogeneity among patients, it is crucial to accurately describe an individual's molecular profile to understand the molecular biology of their disease and develop tailored precision medicine treatments. Each patient's unique molecular signature is now being digitized through multi-omics profiling, which includes genomics (whole-genome sequencing [WGS], whole-exome sequencing [WES]), epigenomics (e.g., ATAC-seq), transcriptomics, proteomics, metabolomics, and microbiome data from individual cells and tissues [37]. Advances in large-scale, population-level data analysis have greatly enhanced our ability to identify disease-related molecular signatures and understand their variability across different patients. RNA sequencing (RNA-seq) is a widely used tool for studying the changes and characteristics of the cellular transcriptome, providing valuable clinical and biological insights for approximately 70% of patients, according to one study [38, 39]. For instance, RNA sequencing analysis of tumor-educated platelets (TEPs) in blood-based liquid biopsies can enable early cancer detection [40]. Platelets isolated from cancer patients exhibit distinct RNA and protein profiles that can differentiate cancer patients from healthy individuals with 96% accuracy and can suggest the location of primary tumors with 71% accuracy [41, 42]. This rapid, accurate, and cost-effective diagnostic approach is suitable for large-scale screening in diverse populations, allowing for the collective analysis of data to identify novel biomarkers specific to particular groups.

Recent advances in sequencing technologies have made genome sequencing faster, more accurate, and cost-effective, particularly with the integration of nanotechnology. One of the most promising examples is single



molecule sequencing (SMS), a third-generation DNA sequencing technology (TGS) that offers revolutionary improvements over second-generation sequencing (SGS) and has seen widespread use [43].

5.2. The therapeutic application of AI with the help of nanoparticles

The primary goal of nanomedicines is to enhance drug delivery efficiency by targeting active drugs to pathological sites while minimizing harm to healthy organs or tissues. Over the past three decades, key principles for designing nanodrugs for cancer treatment have included the enhanced permeability and retention (EPR) effect [44] and the prolonged circulation effect [45]. While both principles have shown effectiveness in human patients, their clinical intensity and relevance are still under discussion [46].

Despite extensive research on cancer nanomedicines in vitro and preclinical studies, only a few nanopharmacological products have been validated in clinical trials, and even fewer targeted anticancer agents have been developed based on specific biomarkers [47]. This suggests that the design of nanomedicines needs to be both drug-specific and nanocarrier-specific (Fig.3). Several critical factors should be considered in nanomedicine design:

- 1) Evaluation of Physicochemical, Pharmacokinetic, and Pharmacodynamic Properties: It is crucial to assess the properties of the delivered drugs to ensure their unique safety and efficacy profiles.
- 2) Tailoring Drug Delivery via Specific Nanocarriers: This involves optimizing the pharmacokinetic distribution of nanocarriers and understanding how this distribution affects the pharmacokinetics of the drugs in vital organs, aiming to improve clinical and immune efficacy.
- 3) Targeted Delivery to Specific Cell Types in the Tumor Microenvironment (TME): Accurate targeting of drugs to the appropriate cell types within the TME is essential for achieving the best possible antitumor effect [48].

Understanding these factors in the early stages of nanomedicine development can lead to more translatable products and more consistent manufacturing processes. Artificial intelligence (AI) can be crucial in optimizing these design strategies and accelerating the development of effective nanomedicines.

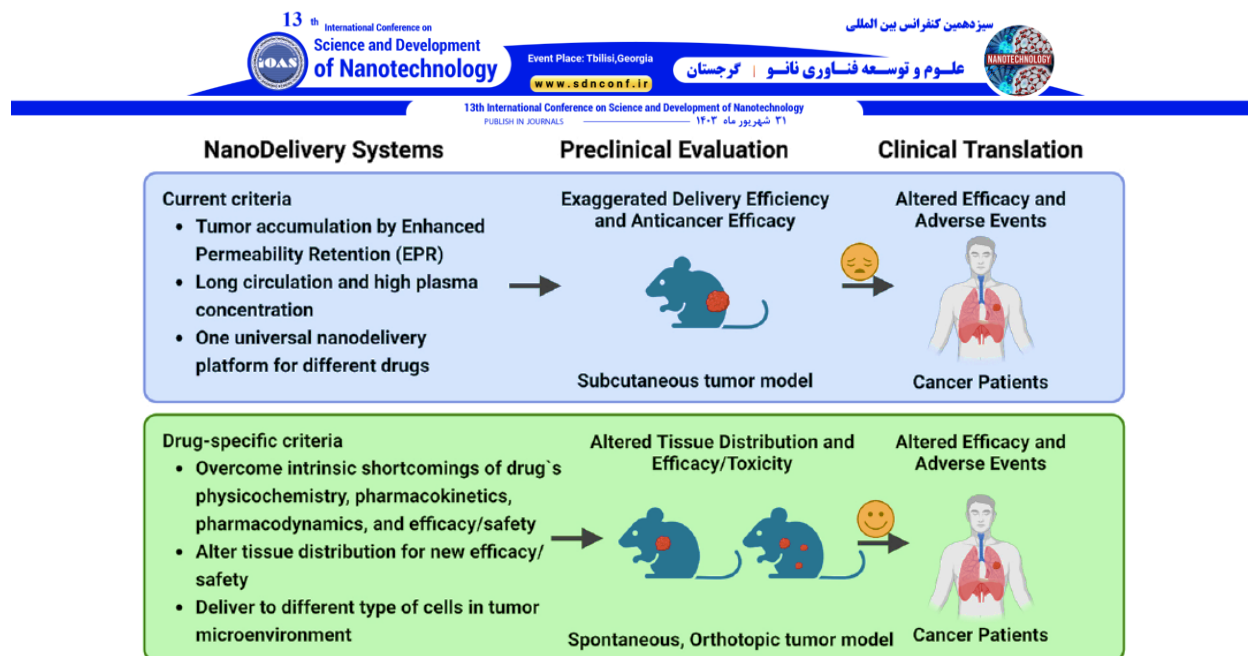


Fig.3 Principles of nanomedicine design

5.3. Application of artificial intelligence in nanotoxicity

Toxicity is a significant hurdle in the clinical application and translation of nanomedicines into clinical trials. Before nanomedicines can be safely used in patients, the intrinsic and extrinsic toxic effects of nanoparticles must be thoroughly understood. Unfortunately, there is no standardized protocol for analyzing the toxicity of carrier materials. Nanoparticle toxicity arises from their interactions with surrounding environments and biological components, influenced by various physicochemical properties such as size, shape, crystal structure, surface charge, surface functionality, and granular phase [50]. The application of artificial intelligence (AI) and machine learning (ML) in predicting and understanding nanotoxicity has been explored in detail by Singh et al. However, evaluating the apparent cytotoxicity of nanodrugs alone is insufficient for ensuring biosafety and minimizing nanotoxicity. To address this, researchers often rely on nanodescriptors—such as microscopic images—to map specific features or integrate multiple characteristics of a nanomedicine [51]. One promising approach is the use of a support vector machine classifier model combined with a genetic algorithm (GA-SVMC) to predict the toxicity of nanomaterials. This model considers properties such as size, surface area, charge, chemical structure, reactivity, and partitioning characteristics. Quantitative structure-activity (QSAR) models can provide valuable predictions of drug properties and can be trained using large datasets. The application of QSAR in classifying nanomaterials and assessing risks, particularly in nano-QSAR, is both advanced and popular [52]. For instance, Liu et al. first used QSAR to investigate the toxicity of carbon nanotubes embedded in bilayer membranes, successfully linking molecular properties to nanomaterial toxicity [53]. In the past decade, various AI-based tools have been employed for the nano-chemical analysis of different nanomaterials, complementing the nano-QSAR approach [50]. However, the field of nanotoxicology still lacks standardization. Different aspects of the interaction between nanomaterials and biological systems can lead to varying levels of toxicity, and there are limited datasets available for in silico modeling, training, and validation.

Furthermore, there is a scarcity of comprehensive datasets for in silico modeling, training, and validation. To address this, a "minimum information standard" has been proposed to investigate nano-bio interactions, which includes detailed information on material specifications, biological specifications, and experimental protocols [54]. Another critical aspect in designing safe nanoparticles is preventing the formation of a



protein corona. Currently, there is no standardized protocol to quantitatively predict protein corona formation. However, integrating ML with meta-analysis has led to the development of a model that predicts protein corona formation with an R^2 greater than 0.75 [55]. This approach enables accurate and quantitative prediction of functional protein compositions in a complex corona, which is closely related to cell recognition (e.g., macrophage uptake and cytokine release) and nanotoxicity, thereby guiding the design and development of safer nanoparticles.

5.4. Nanomaterials and AI to correlate drug dose and therapeutic efficacy

Nanomaterials offer the potential for controlled drug dosing by aligning drug release rates with patient-specific pharmacokinetic and pharmacodynamic profiles. Similar to targeted drug delivery, external stimuli can be used to achieve controlled release. Porous scaffolds that can release targeting agents on demand provide a promising method for precise drug dosing.

Techniques such as electric fields and ultrasound have been employed in both in vitro and in vivo animal models to achieve pulsatile drug release from nanomaterials. This includes the use of electron-sensitive polymer nanoporous membranes and mesoporous silica nanoparticles [56]. However, to further advance personalized dosing technologies, these pulsed-release systems need to be integrated with real-time sensing technologies that monitor drug levels in the plasma or at the target site—similar to how insulin pumps function. This integration presents challenges in developing nanosensor technologies that remain stable and reliable over extended periods.

5.5. Nanomaterials and AI in Precision Diagnosis

Nanotechnology has significantly enhanced the speed and accuracy of sequencing technologies for collecting genetic data. In particular, third-generation sequencing methods, such as Single Molecule Real-Time (SMRT) sequencing, have been extensively explored. The SMRT system utilizes 60-100 nm holes created by electron beam lithography on a 100 nm thin aluminum sheet deposited on a silica substrate [57]. These nano-wells, each containing a single DNA polymerase, serve as confined observation volumes for optically monitoring the addition of fluorescent nucleotides to a complementary DNA strand. This technology's ability to perform real-time data acquisition and sequence long reads allows it to preserve genetic context and overcome challenges associated with sequencing repetitive genetic elements [58].

Nanopore sequencing provides another single-molecule approach for DNA and RNA analysis by measuring changes in ion current as a DNA strand passes through a lipid membrane. A significant advantage of nanopore sequencing is its minimal requirement for nucleotide labeling and sample preparation, in addition to its long-read capabilities. Recent portable nanopore platforms have enabled rapid identification of biological targets, such as the Ebola virus, in remote locations [59]. However, achieving single-nucleotide resolution with protein-based nanopore sequencing remains challenging, as multiple nucleotides can occupy the nanopore simultaneously, affecting the measured ion current. Solid-state nanopores are a potential alternative to protein-based nanopores. In advancing from rationally designed sensors targeting specific biomarkers to pattern-based nanosensors, computational analysis plays a crucial role. This transition necessitates advanced methods for clustering and classifying large datasets. Principal Component Analysis (PCA) is commonly used in electronic data analysis to generate a smaller set of new variables that capture high variance by using a linear combination of input data features. These new variables help classify data into distinct groups [52]. However, PCA is limited to linear combinations, meaning it does not account for nonlinear relationships between variables. In contrast, artificial intelligence methods, such as neural



networks, can capture these nonlinear correlations, increasing data classification accuracy in applications like electronic noses [60].

The implementation of nanosensor arrays for biomarker-free, rapid, and accurate cancer diagnosis and staging holds great promise. However, a significant challenge is the need to collect extensive data from diverse populations to enable effective pattern recognition in nanosensor arrays, which require robust clustering algorithms to account for inherent variations between populations. Alongside efforts to develop efficient nanosensors for detecting markers in liquid biopsies, analyzing tumor tissue remains crucial for the diagnostic process. Many assay technologies are being adapted for rapid biomarker detection in cell cultures. For intracellular detection of target analytes, techniques for cellular penetration are also necessary [61]. Additionally, nanosensors based on pattern recognition, rather than specific biomarker targeting, have been developed for cell culture analysis.

6. Future outlook and challenges of drug delivery using Nano Technologies and AI

The key to treating cancer is early detection. Doctors now have access to high-quality imaging, and skilled radiologists can spot and identify warning signs of abnormal growth. After identification, the next step is to determine whether the tumor growth is benign or malignant by doctors. A reliable method for diagnosis is sampling, which is an invasive method. Nevertheless, there is a possibility of error even after this method. Some healthy people are diagnosed as cancer patients and vice versa. In both cases, there are patient concerns and even the second case causes a delay in treatment.

Researchers are looking to improve the diagnostic process to avoid these issues. The reliable diagnosis of malignant or benign lesions without sampling can be a game changer.

Continuous advances in technology have led to advanced techniques such as artificial intelligence, which have shown promise in the field of drug discovery and optimization. However, nanomedicine has various challenges, despite boasting numerous advantages. The most widely highlighted challenges are the EPR effect, the size and nature of drug delivery systems, drug reservoir design issues, biocompatibility, drug concentrations, and toxicity, among various issues [61-63].

Artificial intelligence (AI) holds significant promise for overcoming various challenges associated with nanotechnology, including data analysis, complex data processing, and the facilitation of drug discovery and design. By integrating AI, it becomes possible to address limitations and enhance precision in dose delivery. In addition, artificial intelligence is very effective in genetic programming and provides complementary information about cancer genomics by identifying various complex patterns. ANNs, fuzzy logic, and decision trees are critical components in modern drug discovery processes [64].

Fuzzy logic-based drug delivery systems have been identified to provide faster response times to achieve effective regulation and automation for drug delivery planning and arterial and venous circulation management using drug agents [64].

Another of the most advanced artificial intelligence solutions that have been considered in silico medicine is reinforcement learning. The main reason is the ability of these artificial intelligence algorithms to learn from their environment and less dependence on data sets. Recently, a study proposed a supervised learning algorithm capable of identifying missing features from the datasets and detecting the differences between normal and diseased patient profiles [65].

The inclusion of artificial intelligence in nanotechnology and pharmaceutical research has significantly reduced the time and cost associated with drug discovery, the evaluation of pharmacodynamics and



pharmacokinetic profiles of various drugs, and the reduction of false positive rates. However, challenges arise in high computational power, availability, maintenance, ethical issues, and reliability of AI-enabled outcomes [62]. Meanwhile, suppose AI is considered for nanomedicine. Challenges like overfitting, correctness, and bias must be addressed to ensure robust models for predicting drug synergism, identifying appropriate molecular combinations, and biomarker imaging that contribute to accurate drug delivery and drug efficacy. Similarly, a common problem is the availability of large datasets with multiple sets of clinical information to train AI models and optimize for accurate drug delivery. Currently, there is a lack of use of AI for drug development and delivery, but in recent years, the pharmaceutical and bioinformatics industries are some of the future areas where the successful integration of AI has been strongly observed. Similarly, AI has been limited in drug delivery, but there is promise in its contribution toward future therapeutic applications to enhance drug delivery [65].

Include the side effects you may experience, depending on the type of targeted therapy you receive and how your body reacts to it. Also, the most common side effects of targeted treatment are liver problems, which can be prevented with the help of artificial intelligence.

7. Conclusion

The field of nanomedicine is rapidly evolving, and versatile drug carriers are being evaluated for their effectiveness in reaching target tumor sites and improving local drug delivery. Furthermore, combining nanotherapies with hybrid approaches is continuously evaluated to enhance treatment efficacy for cancer patients. However, these approaches are confronted by various challenges of conventional drug development and delivery methods.

While it is essential to understand drug synergies, identifying individual patient profiles based on their unique molecular signatures has become critical in ensuring the ultimate success of targeted drug delivery. These are necessities because the rate of treatment failures and lack of response to treatments continue to remain high. At the same time, to improve cancer treatments, more clinical parameters are required to minimize treatment failures and chances of cancer recurrence. In this context, intelligent computational models can process complex data and produce accurate results successfully. Therefore, AI plays a crucial role in devising a roadmap to assess real-time monitoring of drug delivery procedures, classifying patients according to molecular signatures, and providing actionable insights on treatment response, ability to quantify clinical information, and, most importantly, contributing towards image-guided drug delivery due to proven capabilities with clinical imaging. Although several techniques have been evaluated in pharmaceutical and nanotechnology domains over the years, the studies focusing on AI for targeted drug delivery have remained limited.

Therefore, this study aimed to provide a pathway on how Overview Integrating Artificial Intelligence and Nanotechnology in overcome some of the limitations of fabrication techniques and the likely impact on patient profiling, and cancer biomarker detection to help enhance the outcomes of nanotechnology-based therapeutics. Future works may lead to building intelligent solutions for biomarker detection and nanoparticle tracking and analysis systems by taking critical insights from the survey, At this stage, artificial intelligence can be a suitable guide for synthesizing targeted drugs by diagnosing, determining, and performing calculations.



Abstract

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