

Precision Cancer Medicine via the Integration of Nanotechnology and Artificial Intelligence

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Abstract

The domains of artificial intelligence and nanotechnology have played a pivotal role in achieving the objective of precision medicine, which is to customise the optimal course of therapy for individual cancer patients. The recent merging of these two domains is facilitating enhanced patient data collection and nanomaterial creation for precision cancer treatment. A patient-specific illness profile is assembled using diagnostic nanomaterials, and a suite of therapeutic nanotechnologies is subsequently employed to enhance the course of treatment. The logical design of diagnostic and treatment platforms, as well as the analysis of their output, are highly challenging because to the high levels of intra-tumor and inter-patient heterogeneities. By applying pattern analysis and classification algorithms to increase diagnostic and treatment accuracy, the integration of AI techniques can close this gap.

Keywords: artificial intelligence, nanotechnology, big-data, cancer, precision medicine

Introduction

Every patient is different. In addition to our obvious distinctions in blood type, age, gender, height, and eye color, we also have distinct molecular fingerprints. Patients have a range of phenotypic alterations and medication reactions as a result [1]. Precision medicine has advanced through all phases of medical development thanks in part to nanomaterials. Longer sequence read lengths and quick, sensitive single-molecule detection are made possible by new omics collecting technologies like single-molecule nanopore sequencing, which preserves genetic context [2]. The logical design of tailored therapeutic methods that use both endogenous and exogenous triggers for enhanced drug distribution has been made possible by advancements in nanomedicine manufacturing techniques and a growing understanding of cancer biology. These developments also aided in the creation of theragnostic nanomedicines, which combine a medication with an imaging tool to assess the effectiveness of therapy

internally in the patient's body [6]. An method in AI called machine learning (Box 1) uses massive databases of prior instances to train an algorithm. Among other things, it's used to categorize data, identify patterns in it, and identify the best way to solve a given issue. Numerous medical specialties, such as medical imaging and gene expression pattern analysis, have benefited from the use of machine learning and AI more broadly. Designing and implementing nanomaterials is done in nano informatics using AI and other computational techniques.

The enhanced design of nanotechnologies for diagnosis and therapy can benefit from AI algorithms' capacity to analyse massive information and identify intricate patterns. Formulations for nanomedicines can be optimized by predicting how nanoparticles will interact with biological medium, cell membranes, the target drug, and the effectiveness and kinetics of drug encapsulation [4]. Furthermore, patients' medicine efficacy may be predicted and patients' health status can be distinguished using pattern recognition and classification algorithms [5, 6]. Because cancer is so complicated, these analytical skills are particularly important. Using AI to precision medical data analysis and nanomedicine design is highlighted in this study, which covers the use of nanomaterials to the creation of omics, diagnostics, and therapy technologies for precision cancer medicine.

AI and Nanomaterials for Precision Diagnosis

With the advancement of big data analysis of population-wide omics, the technique of identifying pertinent illness biomarkers and their variation and distribution among various patients has undergone significant change. For instance, creating an RNA-based molecular signature that differentiated between the groups allowed for the categorization of patients with localized and metastatic malignancies and healthy individuals. In more than 70% of the instances, the molecular signature—obtained by RNA sequencing of tumor-educated platelets, or blood platelets with changed RNA profiles impacted by platelet-tumor interactions—provided a precise location of the original tumor [7]. Accurate, quick, and reasonably priced data collection instruments are critical to gathering copious volumes of data from a heterogeneous patient group and effectively identifying novel biomarkers.

Sequencing methods used to acquire omics data are made faster and more precise by nanotechnology. Third-generation sequencing techniques—namely, single-molecule real-time (SMRT) sequencing and nanopore sequencing—allow for the direct examination of individual

DNA molecules without the requirement for template amplification, which reduces reading mistakes.[8] The SMRT system is built on thin aluminium sheets that are printed on silica substrates, with 60–100 nm cavities created using electron beam lithography. Sub-wavelength cavities are then used as a limited observation volume for optical monitoring of the insertion of fluorescent nucleotides to a complement strand of the target DNA. These cavities hold a single DNA polymerase [9].

The translation method from the nanopore raw signal to a nucleotide sequence uses artificial intelligence (AI). A family of algorithms called artificial neural networks is frequently applied to nanopore sequencing (Figure 1). An ANN is often made up of layers of interconnected nodes. For nanopores, this means that the weight of each connection is adjusted based on how it affects the output using training data with known output (known oligonucleotide sequences) in order to get optimal outcomes. Since the accuracy rate of current nanopore sequencing techniques is 90%, further post-sequencing computer analysis is needed for read correction. Depending on the degree of DNA coverage, these extra algorithms produce consensus sequences from numerous reads and take advantage of them to boost sequencing accuracy to 97% and beyond.

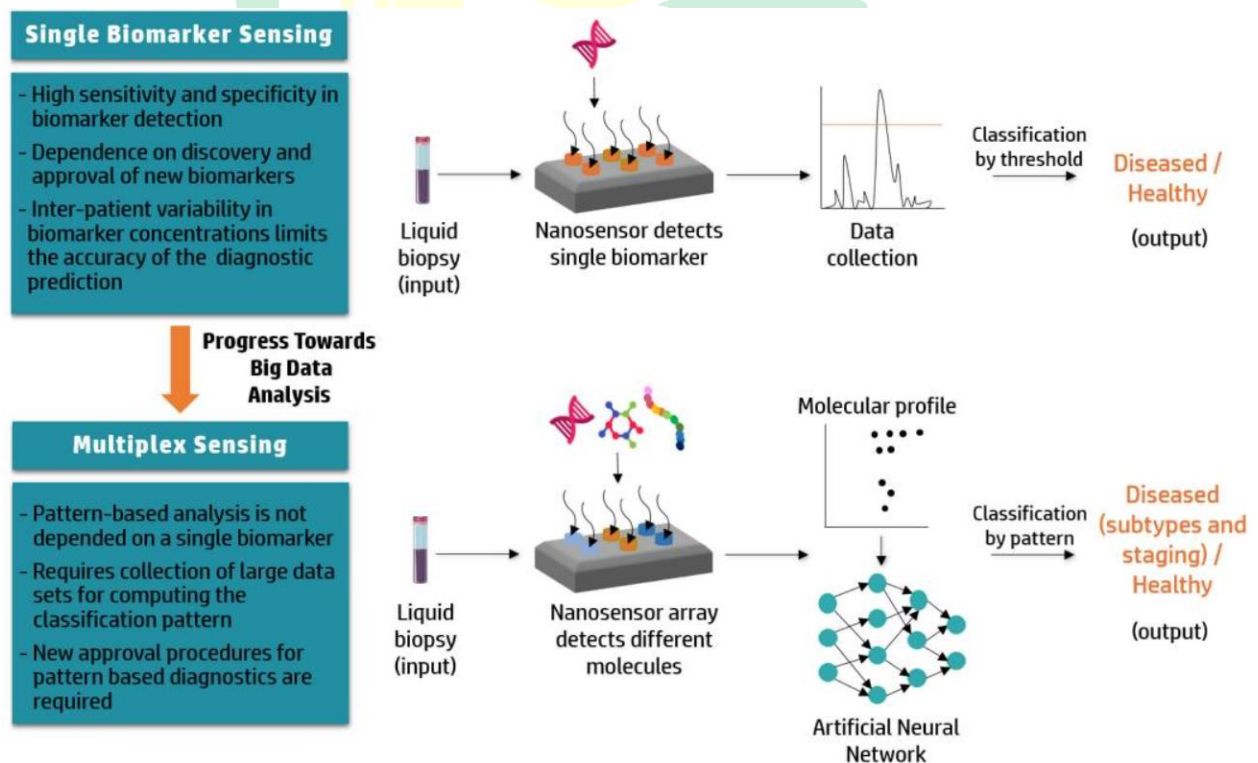


Figure 1



Advancing multiplex sensing from single biomarker sensing. High sensitivity and specificity are demonstrated in the diagnostic screening of patient-derived liquid biopsies using single biomarkers sensors; however, the limited number of authorized single biomarkers and inter-patient variation in biomarker expression pose challenges to this approach. The detection of disease-specific biomarker patterns is made possible by the integration of AI into the data processing of multiplex nano sensors, which are capable of detecting numerous target molecules. By utilizing these patterns, patient screening may be conducted despite the fluctuations in biomarker expression. Additionally, pattern-recognition-based nano sensors were designed for cell culture analysis instead of biomarker targeting. These sensors include arrays of fluorescently-labelled nanoparticles that may selectively identify cancer stem cells in a tumour-derived cell culture and electronic noses that sense the headspace of cell cultures.

Predicting Personalized Drug Potency using Nanotechnology

An avenue to carry out these kinds of in situ diagnostics is using nanotechnology. It is possible to forecast a drug's effectiveness in a patient's tumor by using barcoded liposomes, which are drug-encapsulated particles that have a unique DNA barcode [12]. Currently, this approach's data analysis techniques are dependent on direct barcode counts and their delivered proportion in living and dead cells. By incorporating AI algorithms into data analysis procedures, one may increase the process's scope of application and identify combinatorial treatment effects while accounting for intricate barcode distribution patterns.

Furthermore, the outcomes of the in-situ nano-based screening can be further enhanced by using computational techniques for in silico drug screening as a first step. (Figure 2)[13] The foundation of this approach is a hybrid decision tree that, after being trained on historical data, tests a subset of characteristics. Subsequently, a dataset of medications that are already on the market and can target these cancer drivers was created by analyzing drug-target interactions. This was done in order to automatically adapt therapeutic agents to each patient's unique mutational landscape. This computational technique provides a new perspective on potential therapeutic methods, despite its drawbacks, which include potential mistakes in mutation categorization, a disregard for the combinatorial impact of medications, and intra-tumor heterogeneity.

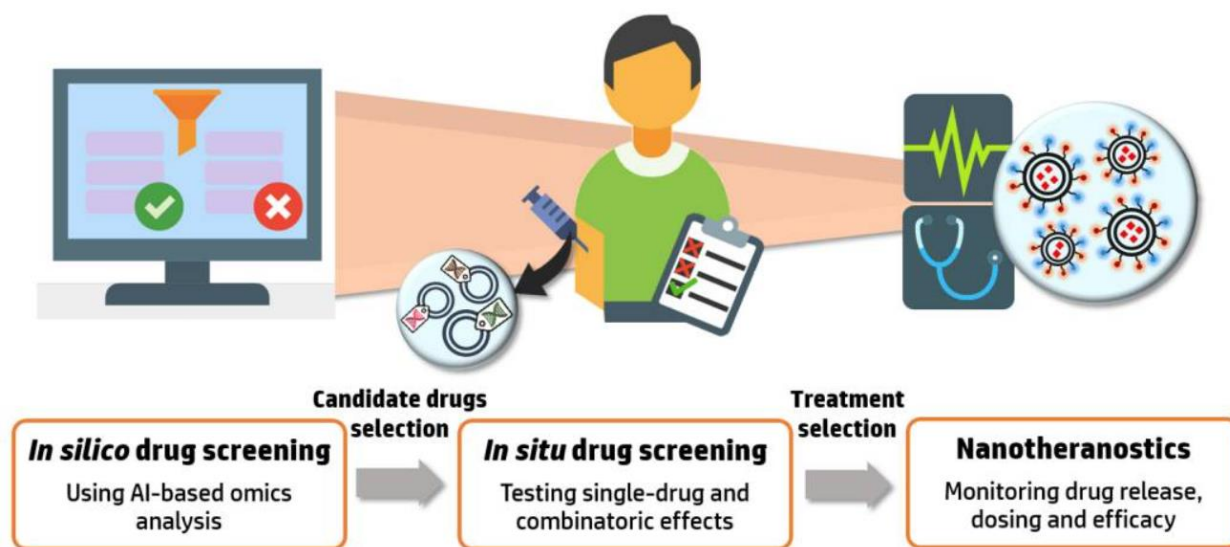


Figure 2

Using nanomedicine and AI to customize a treatment plan for each patient. A list of medications with therapeutic potential will be produced by preliminary drug screening using computational techniques based on the unique omics profile of the patient. Subsequently, in situ testing of these medications using nanoparticle-based technologies can be used to determine the best course of therapy. By monitoring the drug's pharmacokinetics and release at the target location, the treatment regimen may be adjusted through the use of nanotheranostic technologies, which combine the nanomedicine with an imaging agent.

The Use of Nanotechnology in Personalized Gene Therapy

For oligonucleotides to be successfully delivered and activated at the target region during gene therapy, nano-carriers are essential. Since its initial demonstration by Fire and Mello, gene silencing by RNA interference (RNAi) has been utilized to target complementary mRNA molecules in cells and cause their disintegration. Precision medicine for a number of illnesses, including cancer, has made use of this technique [14]. In several cancer types, it has been demonstrated that silencing oncogenes, proteases involved in cell invasion and metastasis, drug resistance-related genes, and angiogenic factors has beneficial therapeutic benefits [15].

RNA interference is not the only way that nanotechnology is being used to deliver gene therapy. Clinical trials are actively testing the delivery of mRNA vaccines and mRNAs for immune-oncology for a variety of malignant disorders, such as pancreatic, colorectal, and metastatic melanoma [16]. In addition, the discovery and advancement of CRISPR (clustered regularly interspaced short palindromic repeats)/Cas9 technology offers an additional genome



editing technique that may be applied to cancer therapy and requires effective delivery methods. Liu et al. knocked out T-cell genes known to cause immunogenic graft-versus-host responses in an effort to produce allogenic chimeric antigen receptor (CAR) T-cells. Even though the activities of these cells were similar to those of unmodified CAR T-cells, more research is necessary to determine how immunogenic these cells are.

However, this data may be used to train machine learning algorithms and identify important design elements that may have gone unnoticed in earlier iterations. Furthermore, particular modelling of the interactions between membranes and nanoparticles can shed light on the particle's uptake mechanism and intercellular route, as well as how the characteristics of the nanoparticles affect these processes. The transfection effectiveness of the nanoparticles can be further enhanced by accounting for these factors and modifying the nanoparticle's characteristics.

Prospects for the Future

Nano sensors that are easy to use and portable can enhance the way cancer patients' follow-up procedures are carried out. The development of flexible, self-healing nanomaterials should open the door to the development of electronic skin nano sensors, which will allow for the ongoing monitoring of specific biomarkers through non-invasive blood testing, salivary analysis, and perspiration. In a recently published work, Gao et al. built and linked a flexible sensor array via Bluetooth to a mobile app for sweat metabolite and electrolyte monitoring. This on-body nano sensor was utilized to track the sweat profiles of subjects in real time across a range of physiological circumstances [17]. Furthermore, the combination of smartphone integration and microfluidic methods in point-of-care devices can also be crucial for streamlining patient-operated devices that will enable more frequent follow-up without adding to the workload on medical teams.

A further new strategy to increase precision medicine's accuracy is the creation of customized computer models for each patient. In an effort to shed light on the patients' unique pharmacodynamics, Bordbar et al. created customized computer models for cellular metabolic kinetics. The metabolite concentrations in erythrocytes and the plasma that was taken from each individual were measured many times, which set the basis for these models. Through the use of these observations, the baseline levels of metabolites and a single rate constant representing a combination of the metabolic network's kinetic constants were computed. Drug

tolerability problems in some individuals were discovered using simulations of how each model reacted to the medication ribavirin, which is used to treat Hepatitis C therapy [18]. By creating a combinatorial treatment plan that targets many pathways at once for each patient, customized drug-tailoring approaches and precision diagnostic platforms can greatly enhance the utilization of already available medications. This will increase therapeutic efficacy and allow for the defeat of medication resistance. The creation, architecture, and use of these nanotechnologies will heavily rely on AI and other computational models.

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