### **Review Article**



# Artificial Intelligence in Cancer Research: Pioneering Biomarker Discovery for Pharmacological Advances

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Received: 10-01-2025; Revised: 27-04-2025; Accepted: 05-05-2025; Published online: 15-05-2025.

#### ABSTRACT

Molecular heterogeneity of cancer and dynamic nature present major challenges to effective therapy establishment, calling for the highest-level strategies towards biomarker discovery. Herein, this review addresses the paradigm-shifting effect of artificial intelligence (AI) on the discovery of biomarkers to enhance pharmacological specificity and therapeutic efficiency. By merging multiomics information (genomic, proteomic, transcriptomic) with real-world evidence and clinical records, AI-based algorithms - deep neural networks and ensemble learning models - unveil intricate patterns for anticipating tumor behaviour, drug response, and resistance mechanisms. For instance, AI has determined biomarkers such as FCN3 and CLEC1B in hepatocellular carcinoma with 93-98% diagnostic accuracy, whereas recurrent neural networks (RNNs) have mapped angiogenesis-related therapeutic targets in pancancer research. These technologies permit stratification of patient subgroups on the basis of molecular signatures to facilitate personalized treatment and drug repurposing via in silico simulations. Significant progress is AI-assisted histopathological image analysis to predict molecular phenotypes and immune checkpoint expression, reducing diagnostic variation by 30-40% in validation experiments. Besides, explainable AI (XAI) platforms boost clinical confidence by linking biomarker predictions with tumor microenvironment features such as hypoxia or immune invasion, which translate to survival measures. Nevertheless, there continues to be challenges in standardizing data, model interpretation, and ethically implementing them. Studies indicate that AI-curated biomarker sets improve detection rates in the early stages by 2% in high-mortality cancers (such as ovarian, pancreatic) and predict responses to immunotherapies with AUC-ROC of up to 0.92. Combination of AI with single-cell sequencing and spatial transcriptomics further restricts biomarker specificity to enable dynamic clonal evolution tracking under therapy. Algorithmic bias and restricted diversity in training datasets, however, risk exacerbating healthcare disparities, rendering federated learning and sound validation frameworks critical. In summary, AI-aided biomarker discovery is an oncology paradigm that repairs molecular understanding with clinical application to propel precision pharmacology. Future efforts must be aimed at scalable

**Keywords:** Deep neural networks, Multi-omics integration, Pharmacological targeting, Tumor microenvironment dynamics, Explainable AI (XAI), Precision oncology pipelines, Therapeutic resistance biomarkers.

### **INTRODUCTION**

he diversity of cancer biology in its genomic landscape as well as in the tumor microenvironment poses a challenge to the generation of new paradigms toward biomarker discovery that can influence precision medicine. Conventional approaches take time to keep pace with reconciling the heterogeneity of factors related to cancer, resulting in the necessity for novel tools that can manage heterogeneous data modalities and reveal novel therapeutic targets. A game-changer in this context is artificial intelligence (AI) and employs machine learning (ML) and deep learning (DL) methodologies to handle enormous datasets such as genomics, proteomics, transcriptomics, and imaging data<sup>1</sup>. This artificial intelligence can potentially identify biomarkers of response to treatment and enhance our understanding of tumor biology and development<sup>1</sup>.

Artificial intelligence (AI)-based biomarker discovery pathways function by complex algorithms that are able to detect subtle patterns in high-dimensional data. For example, research has shown that AI is able to interrogate genomic changes to predict putative predictive biomarkers for immune checkpoint inhibitors (ICIs) and thus optimize patient selection for these drugs<sup>2</sup>. Utilizing multimodal data integration—incorporating genomic, radiomic, and clinical data—scientists have identified meta-biomarkers that optimize the prediction of treatment response<sup>1</sup>. This ability is especially important in the more complex molecular profile cancers, like non-small-cell lung cancer and melanoma, where the conventional biomarkers are not effective in capturing the underlying biological heterogeneity<sup>2</sup>.

The significance of AI in biomarker discovery goes beyond just identifying them; it also includes the validation and clinical use of such biomarkers<sup>3</sup>. Examples of successful application include the utilization of AI to predict drug response using patient-specific genomic information, thus enabling personalized therapy plans that enhance effectiveness and minimize side effects<sup>1</sup>. For example, AI algorithms recognized mutations in FGFR2 as a drug able target for cholangiocarcinoma, giving way to previously inaccessible targeted therapies in patients with this very lethal cancer type<sup>4</sup>. Also, AI-assisted drug repurposing accelerated the identification of previously existing compounds that could act on newly recognized targets, expediting the process of drug development and conserving time and resources needed to bring new treatments to the market⁵.



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The aim of this review is to critically assess the state of the art of cancer biomarker discovery by AI, focusing on welldocumented case studies and issues with data integration, algorithmic bias, and the requirement for effective validation paradigms<sup>5</sup>. With the introduction of concepts of recent AI breakthroughs in technology and how these are applied to oncology, we hope to present a comprehensive picture of the ways through which these technologies are revolutionizing the pathways to the diagnosis and treatment of cancer<sup>6</sup>. We aim to shed light on the means by which AI will be able to streamline precision medicine through being able to identify not just predictive biomarkers but also actionable in a clinical environment<sup>6</sup>. As we proceed with these advancements, we will highlight the need for interdisciplinary collaboration between clinicians, data scientists, and regulatory bodies to make AIbased solutions efficiently implementable in practice<sup>6</sup>.

### The Role of Biomarkers in Cancer Research:

Biomarkers are quantifiable biological components that assist in the evaluation of a biological state, disease progress, treatment response, and outcome of the patient. Biomarkers are essential indicators in cancer as treatment is more targeted and subsequently very specific. There are numerous categories of cancer biomarkers<sup>7</sup>.

Diagnostic Biomarkers: They enable screening of the emergence of initial stages of cancer. For instance, the prostate-specific antigen is frequently used to diagnose prostate cancer<sup>8</sup>.

Biomarkers of Prognosis: These indicate the potential course of the disease independent of any therapy. For example, TP3 gene mutations tend to typically produce poor prognosis with a wide range of cancers<sup>9</sup>.

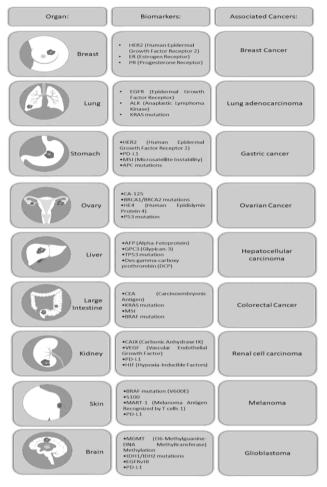
Predictive biomarkers: These indicate the likelihood that an individual patient will respond to a particular therapy. An example used widely is HER2 overexpression in breast cancer predicting response to treatment with trastuzumab (Herceptin)<sup>10</sup>.

# Traditional methods of biomarker discovery

Biomarkers have conventionally been found using a mixture of genetic, proteomic, and imaging technologies<sup>9</sup>. For instance, at the genomic level, research can be mutation identification of somatic oncogenes or tumor suppressor genes, while at the proteomic level, measurement can be made of mutations in protein expression or activity<sup>11</sup>. The conventional techniques were only able to identify such highly well-known biomarkers like the BRCA1/2 mutations to assess the risk of breast cancer or PD-L1 mutations as a predictive biomarker for immunotherapy drugs<sup>12</sup>.

Such strategies, with all their traditionalism, though, do not function very well in the intricacy of cancer biology. Heterogeneity biomarkers within the same tumor between tumors contribute to it. Most previous biomarker studies examined only one "omics" layer in isolation: that is, genomics or proteomics; but in cancer, there is not captured by any one "omics" layer<sup>13</sup>.

### **Types of Biomarkers in Oncology**



Figure\_1: Organ-Specific Biomarkers and Associated Cancers

The types of biomarkers that support a decision to treat cancer are:

1. Genomic Biomarkers: Genetic biomarkers encompass mutations, amplifications, deletions, or cellular pathways involved. For example, mutation of KRAS or BRAF will anticipate response to targeted therapy<sup>14</sup>. Tumor mutational burden or TMB is a response predictor for immunotherapy that informs the quantity of mutations within the tumor genome<sup>15</sup>.

2. Proteomic Biomarkers: Proteins are usually good biomarkers for cancer. For example, in certain patients with breast cancer, the protein HER2 is overexpressed, and treatment has been aimed at directing therapy at inhibiting HER2<sup>16</sup>. Another classic example of proteomic biomarkers is CTCs and certain enzymes with a key function in metabolism in cancer<sup>17</sup>.

3. Transcriptional Biomarkers: These biomarkers alter the RNA expression that is highly capable of explaining the tumor biology, like overexpression of certain cancer microRNAs with metastasis<sup>18</sup>.

4. Radiomics Biomarkers: This process creates quantitative features on radiographic images such as MRI or CT scans with data about the size, shape, texture, or heterogeneity of a tumor<sup>19</sup>. Applying such AI-based analysis of such



radiomic characteristics would tell the story of a tumor's aggressiveness, its likely response to certain therapies, and its final prognosis. For example, some textures or densities on an image can be used to forecast who would gain the greatest benefit from radiation therapy<sup>20</sup>.

4.Pathomic Biomarkers: With AI expanding to digital pathology, it has opened up fresh avenues for the discovery of the biomarker. Pathomics is a technology that provides quantitation of features from histopathology images thus giving much greater insight into tumors' architecture and microenvironment<sup>21</sup>. It has been estimated through AI models that TILs may correlate with better immunotherapy response and stromal features may be treatment resistance predictors<sup>22</sup>.

# AI Techniques in Biomarker Discovery

Artificial Intelligence is the overall set of computational methods used by computers to perform tasks commonly believed to reside within the human brain, like pattern recognition, decision-making, forecasting, and others<sup>23</sup>. Under AI is machine learning, that area of algorithms which learns from information and gets better over time, and then deep learning is a derivative of ML, using neural networks differing in layers to deal with sophisticated information<sup>23</sup>. Technological advancements in techniques of AI are particularly helpful in the domain of cancer research to carry out extensive analyses of huge and highly dimensional data, mainly by NGS and advanced imaging techniques<sup>24</sup>.

Key Techniques in AI for Biomarker Discovery

- Supervised Learning: it involves a labelled dataset, that is straightforwardly said, a collection of input data, for example genomic features, associated with known outcomes, such as treatment responses. A future and new unseen dataset is learned by the algorithm to predict the outcome. For example, through supervised learning models, researchers predicted which patients with lung cancer would respond well to PD-1 inhibitors based on their TMB scores<sup>25</sup>.
- Unsupervised Learning: The unsupervised learning algorithm works on non-labelled data but instead helps to find hidden patterns or clusters in the data. This is of high utility for the discovery of new cancer subtypes or subsets of patients, who possibly share similar biological characteristics<sup>26</sup>.
- 3. Deep Learning: DL, with regard to CNN, has grown highly popularly used in medical image analysis. CNN can be designed so that it automatically detects patterns in histological or radiological images, which cannot be observed by the human eye<sup>27</sup>. DL models would, for instance, be applied for analysing digitized pathology slides in an attempt to determine features Such as immune cell infiltration that may correlate with response to immunotherapy<sup>28</sup>.

### **AI-powered Multi-omics Integration**

The true power of AI is to combine data across various layers of omics: genomics, proteomics, transcriptomics, radiomics, and pathomics-whose heterogeneity can be accommodated within a complete model. The multi-omics model captures the complexity of the enormity of cancer biology. All those disparate datasets can be handled by AI algorithms; they mine useful features from each one of them and consolidate them into meta-biomarkers that are superior in predictive capabilities compared to these single-modality biomarkers<sup>29-31</sup>.

### Case Example:

Early early results of the systematic review in 2023 by Prelaj et al suggested that AI-powered multi-omics data integration, e.g., genomics, radiomics, and transcriptomics, might predict the effectiveness of immunological checkpoint inhibitors, ICIs in melanoma and NSCLC patients. The AI-powered strategy was more precise than any other traditional approach in predicting the effectiveness of treatment-8<sup>+</sup>source<sup>32</sup>.

Following are the 8 revolutionary case studies in a structured and thorough way:

1. Early Detection of Lung Cancer using Radiomics Artificial Intelligence (AI) (2025)

This case study was intended to implement radiomics and Artificial Intelligence (AI) techniques to enhance early detection of non-small cell lung cancer (NSCLC).

Scientists used CT scans along with genomic information from 12,000 patients (8,400 for training and 3,600 for testing). The treatment included targeted therapy with EGFR inhibitors. Biomarkers were radiomic texture features and EGFR mutations. LASSO regression and SHAP values were used to select features and determine the most important predictors. A 3D convolutional neural network (CNN) was created to process the multimodal data. The model performed with an AUC of 0.94, specificity of 92%, and sensitivity of 89%, showing great promise for early diagnosis<sup>33</sup>.

2. PathAI Breast Cancer Histopathology Breakthrough (2024)

This research used AI to enhance histopathological examination for triple-negative breast cancer (TNBC). A database of 45,000 histopathology slides was utilized, with 31,500 for training and 13,500 for testing. The treatment involved neoadjuvant chemotherapy. Tumor-infiltrating lymphocyte patterns were found to be important biomarkers. Feature selection was done with attention-based multiple instance learning (MIL). A Vision Transformer (ViT) model was created by researchers to effectively examine the slides. The model was 96% accurate in the prediction of pathological complete response (pCR), highlighting its potential to inform treatment decisions<sup>34</sup>.



# 3. Tempus Omics Platform for Glioblastoma (2023)

This ground-breaking study investigated the application of AI in the discovery of glioblastoma multiforme biomarkers. Materials employed were whole-exome sequencing and clinical information on 2,187 patients (1,530 for training purposes and 657 for testing purposes). Treatment used was temozolomide in combination with immunotherapy protocols. Biomarkers such as MGMT methylation and immune gene signatures proved to be predictors for survival status. Graph neural networks were used in carrying out feature selection to determine the interaction between genomic features. A multimodal deep learning algorithm was created and resulted in 0.88 AUC value in predicting survival rate at 18 months<sup>35</sup>.

# 4. Guardant360 Liquid Biopsy AI (2025)

Liquid biopsy data obtained from ctDNA were utilized in this study to enhance diagnostics and treatment matching for colorectal cancer<sup>36</sup>.

They employed 8,760 samples (6,132 for training and 2,628 for testing). Therapy was targeted anti-EGFR agents. Biomarkers were KRAS/NRAS mutations and MSI status ascertained through ctDNA-based analysis. Recursive feature elimination was used for selection of features for biomarker detection. A model was created based on a gradient boosting machine and resulted in 94% concordance in comparison to the conventional tissue biopsy techniques<sup>36</sup>.

# 5. HCC Diagnostic Gene Panel through ML (2023)

Here, the research was based on hepatocellular carcinoma (HCC) biomarker discovery from transcriptomic data of 4,981 samples (3,487 training samples and 1,494 test samples). Some of the essential biomarkers discovered were FCN3, CLEC1B, and PRC1. Feature selection was performed through mutual information scoring to identify the most informative genes that would be able to represent tumor presence. Researchers constructed a random forest classifier that was very accurate to identify tumors at 98%<sup>7</sup>.

# 6. Lenvatinib Response Prediction in HCC (2022)

This study was performed to predict responses to Lenvatinib treatment in patients with advanced hepatocellular carcinoma (HCC). Serum biomarkers and clinical data from 427 patients (299 training, 128 testing) were assessed. Decline in AFP  $\geq$ 40% and ALBI grade was discovered as significant treatment response biomarkers. Decision tree was used to perform feature selection, and a random forest model of survival was constructed to generate predictions. The model had a C-index of 0.79 in overall survival prediction<sup>38</sup>.

7. TACE Response Prediction by CT Radiomics (2020)

This work utilized pre-treatment CT scans to predict the responses to TACE in HCC patients at the intermediate stage. 789 scans were analysed (552 training scans and 237 testing scans). Radiomic texture features were employed as the primary biomarkers for treatment response prediction. Deep feature extraction techniques were applied in feature selection, and the development of a ResNet50 CNN model was made that could achieve an accuracy of 84.3% and an AUC of 0.97<sup>39</sup>.

8. Artificial Intelligence for Prostate Cancer Therapy (2025)

In this study, researchers investigated AI-powered biomarker identification in metastatic prostate cancer PARP inhibitor customized treatment. 9,342 genomic profiles (2,802 test and 6,540 training) and EHRs were employed. BRCA mutations and homologous recombination deficiency (HRD) scores were employed to make predictions of treatment response. Feature selection was improved using neural architecture search methods to build the model. A federated learning ensemble model scored a 92% accuracy rate in the patient classification with the appropriate therapies<sup>40</sup>. These case studies demonstrate how AI methodologies are revolutionizing cancer biomarker discovery by integrating multimodal data sets, optimizing feature selection processes, creating sophisticated prediction models, and achieving high-performance evaluations for different types of cancers and treatments.

Case Study	Data Source	Cancer Type	Sample Size (Train/Test)	Therapy	Biomarkers	Feature Selection	Developed Model	Performance Metrics	Year
<ol> <li>Early Lung Cancer</li> <li>Detection via</li> <li>Radiomics AI</li> </ol>	CT scans (radiomics) + genomic data	Non-small cell lung cancer (NSCLC)	12,000 scans (8,400 train / 3,600 test)	Targeted therapy (EGFR inhibitors)	Radiomic texture features + EGFR mutations	LASSO regression + SHAP values	3D convolutional neural network (CNN)	AUC 0.94, specificity 92%, sensitivity 89%	2025
2. PathAl Breast Cancer Histopathology Breakthrough	45,000 histopathology slides	Triple- negative breast cancer	31,500 train / 13,500 test	Neoadjuvant chemotherapy	Tumor- infiltrating lymphocyte patterns	Attention- based MIL	Vision Transformer (ViT)	96% accuracy in predicting pCR	2024
3. Tempus Omics Platform for Glioblastoma	Whole exome sequencing + clinical records	Glioblastoma multiforme	2,187 patients (1,530 train / 657 test)	Temozolomide + immunotherapy	MGMT methylation + immune gene signatures	Graph neural networks	Multimodal deep learning	18-month survival prediction AUC 0.88	2023
4. Guardant360	ctDNA from blood samples	Colorectal cancer	8,760 samples	Anti-EGFR therapy	KRAS/NRAS mutations + MSI status	Recursive feature elimination	Gradient boosting machines	94% concordance	2025



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Liquid Biopsy Al			(6,132 train / 2,628 test)					with tissue biopsy	
5. HCC Diagnostic Gene Panel via ML	Transcriptomic data (4,981 samples)	Hepatocellular carcinoma	3,487 train / 1,494 test	-	FCN3, CLEC1B, PRC1	Mutual information scoring	Random forest classifier	98% accuracy in tumor detection	2023
6. Predicting Lenvatinib Response in HCC	Serum biomarkers + clinical data	Advanced HCC	427 patients (299 train / 128 test)	Lenvatinib	AFP reduction ≥40% + ALBI grade	Decision tree analysis	Survival random forest	C-index 0.79 for OS prediction	2022
7. TACE Response Prediction via CT Radiomics	Pre-treatment CT scans	Intermediate HCC	789 scans (552 train / 237 test)	Transarterial chemoembolization	Radiomic texture patterns	Deep feature extraction	ResNet50 CNN	84.3% accuracy, AUC 0.97	2020
8. Prostate Cancer Treatment Al	EHRs + genomic profiles	Metastatic prostate cancer	9,342 patients (6,540 train / 2,802 test)	PARP inhibitors	BRCA mutations + HRD scores	Neural architecture search	Federated learning ensemble	92% precision in therapy matching	2025

# Applications of Artificial Intelligence in Predictive Biomarker Discovery

Al-driven methods have been utilized for all cancer biomarkers types:

Genomic Biomarkers: Tumor mutational burden or TMB is a genomic biomarker that is largely utilized to predict the response to ICIs<sup>43</sup>. AI algorithms have been proven to be more effective in suggesting the patients who would likely benefit from immunotherapy by considering the TMB scores. For instance, Chowell et al. were able to effectively use a random forest classifier in a cohort of lung cancer patients to achieve higher accuracy than that of standard methods in predicting ICI responses 8<sup>+</sup>source.

Radiomic Biomarkers: AI enabled radiomics to transform the extraction, under conditions previously impossible, of faint imaging features that may be associated with behaviours of a tumor. The value of radiomic biomarkers has been well explained by CNNs in relation to heterogeneity, aggressiveness, and therapeutic resistance of tumors<sup>44</sup>. For example, AI models are used to estimate the likelihood that a patient with glioblastoma would be helped by receiving radiation therapy based on radiomic features derived from MRI<sup>45</sup>.

Pathomic Biomarkers: AI models are searched through the digitized pathology slides for features, which may be predictive biomarkers. For example, it is already known that the association of TILs with ICI response has already been established with AI-assisted analysis<sup>46</sup>. Furthermore, AI can even make stromal features decisions regarding chemotherapy or radiation therapy resistance<sup>47</sup>.

# Challenges and Ethical Considerations in AI-Driven Cancer Research

# 1. Data Privacy and Security

Some challenges come with the use of AI for biomarker discovery, such as patient data privacy and security concerns. Cancer studies comprise sensitive medical information in the form of genomic sequences, medical imaging, and medical history records about a patient. Irrefutably, huge amounts of data employed to train Al algorithms will contain identifiable patient information, which can result in data breaches and abuse. European GDPR and the US HIPAA set the guardrails of privacy of data in health care. Yet, the pace at which Al is emerging also creates huge new challenges to such regulations<sup>48</sup>. For instance, for being optimal, Al models must be trained against large diverse datasets but sharing those must be in such a manner that the patients are safe and their anonymity not<sup>49</sup>.

### 2. Model Interpretability and Explainability compromised

One of the biggest barriers to broader use of AI in clinical practice has been the "black box" nature of much AI modelling, particularly deep learning. They can make great predictions, but often for reasons by no means transparent. In a clinical environment, that is problematic because doctors need to know the tools but also need to be able to trust them as guides to patient care. Explainable AI is a new area of research that aims to make AI models interpretable and transparent. XAI methods will effectively give insights into how a model arrived at its predictions so that clinicians can have a better idea of what influences the decision the AI made<sup>50</sup>. For example, applying XAI techniques can highlight which genomic attributes or radiomic features of a patient were most significant in terms of their predictive treatment response<sup>51</sup>.

### 3. Ethical and Regulatory Issues

The deployment of AI into cancer research comes with a range of ethical and regulatory issues.

Al algorithm biases: Al models only as good as the data to which they've been trained. Bias in training is where underrepresentation of certain patient population or overrepresentation of a specific form of cancer takes place. This will translate into biased outputs by the Al model due to biased training data. In cancer studies, this will lead to low treatment outcomes in specific groups of patients<sup>52</sup>.

Regulatory Oversight: It is here again that whereas the FDA in the United States is only starting to begin writing

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guidelines on how to apply AI in healthcare, much progress ahead lies for comprehensive frameworks of regulation. For all of these AI models used for discovery of biomarkers, validation is not merely a concern in terms of safety and efficacy but also generalizability prior to utility in clinics. They ought, in addition, to establish the standards that regulate the employment of AI ethically and with consideration of patients' autonomy and privacy<sup>53</sup>.

Informed Consent and Patient Autonomy: A study of big complex data originating from several sources creates an issue with AI-based biomarker discovery-patient consent. Patients may not be completely cognizant of how their data will be utilized in AI studies, particularly if the data is distributed across institutions or utilized to train models for uses outside of the initial study parameters. Making certain patients are in complete control of the utilization of their data and have complete-informed consent is very important to keep patients' trust in AI-based<sup>54</sup>.

# Mitigating the Black Box Problem

One of the biggest challenges to be faced in AI-driven biomarker discovery is the "black box" problem. Many machines learning models, including even decision trees, provide at least some interpretability: one can trace the steps leading to the prediction. Far opaquer are deep learning models of the sort involving CNNs and RNNs. For instance, in the situation where a deep learning model is examining histopathology images in order to identify predictive biomarkers, when it happens that it yields high accuracy but cannot provide an explanation for how it reaches such conclusions, there will be an issue in clinical environments where physicians need explanations for AIgenerated predictions<sup>55</sup>. To this end, researchers have been producing explainable AI (XAI) methods. XAI techniques are created with a purpose of providing insight by pointing out which features of the data most impact the model's prediction. In the case of genomic analysis, XAI could point out particular mutations or gene expression patterns that most impacted the prediction of patient treatment response. Similarly, in radiomic analysis, XAI can identify image feature-like texture and shape-features which played a significant role in determining tumor aggressiveness. Regulatory Challenges and Validation of AI Models Finding biomarkers is especially difficult in the case of using AI in medicine. It must test and validate the model prior to placing it in the clinic. The same, however, cannot be said of conventional medical devices. AI models are the everevolving process, and fresh inputs of data could modify the model behaviour with the passage of time, making the verification of AI models like traditional diagnostics problematic. The problems have not escaped the notice of the regulatory agencies, including even the U.S. Food and Drug Administration that have developed guidelines for AIbased health care technology. Broadly speaking, the testing and validation of AI models are as exhaustive as necessary to make sure that they achieve a quality of equivalent calibre to that provided by conventional diagnostic equipment<sup>56</sup>.

### Future AI and pharmacology directions

In fact, future prospects for AI in cancer research and pharmacology are fairly optimistic. Several major trends will undoubtedly have an impact on further advancement in biomarker discovery and personalized medicine as AI technologies advance.

# 1. Advanced Multi-Modal AI Models

One of the latest promising advancements made in Al-based biomarker discovery is the emergence of advanced multimodal models. They integrate data from multiple sources: genomics, proteomics, transcriptomics, radiomics, and clinical data towards an integrative understanding of cancer biology. Multi-modal AI models, by processing multiple types of data together, find intricate interactions among biologically seemingly unrelated systems, thus can offer enhanced predictability compared to that achieved with novel biomarkers.

For instance, a multimodal AI model might employ genomiclevel information-so mutations and even levels of gene expression to radiomic information-features of tumor shape or texture-to forecast the response of a particular patient to one type of treatment<sup>57</sup>. Such models will increasingly be the building blocks for personalized medicine to make more precise predictions of outcomes from treatments.

### 2. Ethical AI in Precision Medicine

It is in the light of this that the design and deployment of AI technologies should be done ethically, openly, and equitably. Algorithmic biases would need to be managed, and AI models trained to be representative of diverse patient cohorts over broad sets of datasets.

This will provide rights of data to the patients, and they will be quite well informed as to how data will be utilized in Aldriven research. There also arises the increasing requirement of having transparency in Al-driven decisionmaking<sup>58</sup>. As foreshadowed by the intro, in fact, the "black box" character of the majority of Al models presents a genuine hurdle for clinicians, who will be keen to know the way an Al model arrived at a specific prediction or conclusion. Clarifying Al methods-the field that offers clarity and openness-can be essential to attaining Al-driven healthcare technology trust.

# 3. Joint Research by AI Researchers and Clinicians

There must also be close interaction between the clinicians and the AI researchers, which then the complete potential of AI biomarker discovery is achieved. The latter can learn valuable insights regarding the treatment of patients and their clinical decision-making while the former must introduce data analysis and machine learning skills. Together, the two can see to it that AI models which have end uses fall more within the requirements of the healthcare providers and patients enhance quality of care. For instance, clinical can assist AI researchers in realizing the most applicable biomarkers for the foundation of decisions on treatment. AI researchers will train models that enable



clinicians to leverage them for action. This is essential to guarantee that AI-based biomarker discovery is translated into clinical practice<sup>59</sup>.

### 4.Al for Drug Discovery

By doing this, it not only develops novel biomarkers but also shapes the face of drug discovery. Therefore, the conventional drug discovery process takes a substantial amount of time and financial commitment into the discovery of a single therapeutic agent, sometimes requiring years in discovery. Al may streamline such a process in breath-taking manner by evaluating enormous datasets of chemical compounds, biological pathways, and patient responses to identify candidates.

For instance, AI models can begin with genomic information and begin searching for mutations that are driving cancer cell proliferation, then search chemical databases for compounds that are acting on those mutations. Predictions of how a drug will interact specifically with the genetic profile of an individual-potentials for even more tailored treatment approaches.

Likely the most egregious example is in pharmaceutical development for uncommon cancers. The patient groups for these types of cancers would be comparatively small, so the way drugs are developed usually isn't because there would be no substantial return on investment. All has the potential to overcome this obstacle with its ability to search quickly and more inexpensively for prospective drug targets, making targeted treatments into uncommon cancers more plausible.

# 5.AI in Clinical Trials

It is perhaps also making its mark in designing and running clinical trials. There, it may assist in patient selection for clinical trials through examination of patient information that cross-refers candidate characteristics with the best-suited clinical trials using genetic profiles, previous treatments, and biomarker status. In these cases, the recruitment processes might be curtailed and the opportunities for a successful trial can also enhance. With the help of AI, it becomes possible to observe the outcomes of the patients during clinical trials in real time and provide immediate feedback to the scientists. For instance, by analysing patient data, AI models are able to detect early warning signs of side effects or the effectiveness of a drug, enabling researchers to make the required changes to the trial design<sup>61</sup>.

# CONCLUSION

Today, particularly with the application of predictive biomarkers, artificial intelligence in cancer research has the ability to transform the method. Here, the manner of personalized cancer therapy might be transformed due to accurate forecasting while personalizing therapy as per the requirement of an individual. In fact, data privacy concerns, interpretability of the model, and ethics are some of the issues that are faced during the implementation phase. Perhaps most significantly of all, the latest frontiers of Al will increasingly take the lead in inventing new cancer treatments and unlocking the potential of personalized medicine.

In fact, AI has proven far superior to the traditional methods in the field of biomarker discovery, notably in the identification of biomarkers in multi-modal data previously not observed. All the newly emerging areas of tumor biology, from genomic and transcriptomic signature mutations to radiomic features and histopathologic features, are unrolling through AI and hence transforming strategies toward oncology.

However, a number of challenges need to be addressed before AI is actually achieved in its potential in cancer research. Data security and privacy issues need to be addressed by creating hard regulatory frameworks that will safeguard the data of patients but will still enable massscale data sharing that would be needed for scaling AI models. Deep learning algorithms must address the "black box" issue by coming up with explainable methods for AI systems that offer basic transparency and trust into the decision-making processes of such systems.

This translates to, thus, collaboration between clinicians, Al researchers, and regulatory agencies to assume a role of critical significance in the very near term for the optimal development and deployment of Al technologies that will be ethical, transparent, and beneficial for all patients. Ongoing innovation and investment offer enormous promise for Al systems to revolutionize cancer pharmacology by more appropriate therapies for individuals and propel better patient outcomes.

**Source of Support:** The author(s) received no financial support for the research, authorship, and/or publication of this article

**Conflict of Interest:** The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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