

Role of Artificial Intelligence in Advancing Biotechnology: A Comprehensive Review

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Abstract - The convergence of Artificial Intelligence (AI) and biotechnology is revolutionizing scientific research, healthcare, and industrial applications. This paper examines how AI techniques, like computer vision, machine learning, deep learning, and NLP, are revolutionizing important biotechnology fields like drug discovery, genomics, personalized medicine, agricultural innovation, and industrial bioprocessing. AI enables faster data analysis, accurate prediction of biological behaviors, and automation of complex tasks, significantly accelerating the pace of innovation. We also discuss commonly used AI tools in biotechnology and highlight the growth of AI-driven biotech startups. The incorporation of AI presents a number of obstacles despite its transformative potential, such as the requirement for transparent algorithms, ethical issues, and data privacy concerns. The goal of the article is to provide a thorough review of the state of affairs, recent developments, and potential future progress in the nexus of biotechnology and artificial intelligence.

Keywords: Artificial Intelligence (AI), Biotechnology, Machine Learning

1. INTRODUCTION

The goal of artificial intelligence (AI) is to build machines with intellect comparable to that of humans. constructing models and algorithms that simulate human intelligence to enable computers to perform complicated tasks, learn from data, and adjust to changing circumstances. NLP is one branch of Artificial intelligence that is growing in significance. This technical development provides voice assistants and machine translation applications since it allows machines to understand, interpret, and produce human language. The development of NLP has greatly improved the effectiveness of information transfer between humans and machines. Computer vision, or the capacity of computers to perceive, and analyse visual data from the outer world, is another key purpose.

Consequently, healthcare providers can make better decisions. It enables robots to explore and interact with their surroundings without human assistance. Artificial intelligence (AI) is crucial to robotics. This phenomenon has led to the development of sophisticated robotic systems that are capable of a variety of activities, including product assembly, surgical assistance, and the exploration of hazardous regions such as the deep ocean or space. Artificial intelligence (AI) has demonstrated its versatility and potential in a number of industries, including marketing, banking, and education.

AI is the growth of computer systems that can learn and solve problems—tasks that need human intelligence. The primary objective of ML, a subdivision of AI, is to develop methodologies that let computers study and make decisions based on data. Without being specifically programmed for a given task, these systems gradually enhance their performance, which makes them incredibly adaptable for a variety of uses. The application of AI and ML in biotechnology and biochemistry is transforming traditional techniques by offering tools that can analyze large and complex datasets, identify hidden patterns, and produce accurate predictions.

Machine learning has been a cornerstone of modern drug discovery from the early days of QSAR. Despite this long history, the use of machine learning techniques has lately increased significantly due to the success of deep learning in many application fields. Many cheminformatics and modelling applications, such as virtual screening, chemical production planning, predictive toxicology, and more, have been touched by machine learning. 5, 6 Machine learning techniques are now applicable to protein structures, imaging, text, and transcriptomics data in addition to more conventional data types like chemicals and protein sequences. We are happy to see that this range of goals, data kinds, and approaches is reflected in the works included in this special issue.

2. BIOTECHNOLOGY

Health systems have been profoundly changed by biotechnology, including industrial applications such as enzyme development, green biotechnology (agricultural), and red biotechnology (medical applications). Through ground-breaking discoveries like CRISPR-CAS genome editing, which allows precise genetic alterations to treat diseases like cancer by correcting oncogenic mutations in preclinical research, biotechnology has transformed medicine in the healthcare industry (more specifically, biotechnology).

In the extremely interdisciplinary field of biotechnology, advanced technologies are powered by biological systems, processes, or animals. Biotechnologists frequently manipulate DNA, proteins, and cells from live organisms (Lysunets) to address issues in a variety of domains, including human health, agriculture, and the environment. Although biotechnology has many applications, the medical field is one of the most well-known [1]. For example, industrial biotechnology. Industrial biotechnology, a third wave of biotechnology, is currently booming. Green biotechnology, which focuses on genetically modified crops, and red biotechnology, which targets the medical field, are distinct from industrial biotechnology, commonly known as white biotechnology [2][3]. Biological systems are used in industrial biotechnology to produce minerals, chemicals, and energy. Together with advances in molecular genetics, enzyme engineering, and metabolic engineering, this technology is primarily based on fermentation technology (the controlled use of microorganisms) and biocatalysis (the use of enzymes to catalyze chemical reactions) [4].

3. HISTORICAL CONTEXT OF THEIR CONVERGENCE

A new era of creativity and discovery has been brought about by the confluence of biotechnology and artificial intelligence. Researchers can better comprehend and resolve complex biological problems by combining AI with biotechnological techniques [5]. Genomics is a good example of this convergence since it uses AI methods like ML and DL to assess enormous volumes of genomic data. By learning how genes contribute to various qualities and disorders, researchers can identify algorithms and relationships in genetic sequences [6]. Therefore, the development of targeted therapeutics and personalized treatments can be accelerated by AI-powered genomics research. One area where the two domains overlap is drug discovery [7]. The combination of AI and biotechnology has also led to advancements in synthetic biology, enabling researchers to design novel biological systems that are suited to carry out particular functions. Artificial intelligence could help with the planning procedure by predicting how modifications to DNA will impact the functionality of the creature [8]. It makes it possible to produce biomass, biopolymers, and more effective drug delivery systems. Last but not least, the combination of biotechnology with AI has the ability to revolutionize a number of sectors, including energy, agriculture, drug and environment. By using AI to analyze complicated biological data, scientists may find significant global issues and develop novel remedies.

In the field of medical imaging, deep learning has garnered a lot of interest as a potential remedy for automated, quick, and precise medical image analysis—a critical component of high-quality healthcare. In medical image analysis, convolutional neural networks and their variations are now the most popular and extensively utilized deep learning models. The main functions of deep learning models—classification, segmentation, retrieval, detection, and registration—are thoroughly examined in this work, along with succinct summaries of contemporary deep learning models used in medical image analysis [9].

Recent studies have demonstrated that deep learning models can execute some tasks better than medical specialists. It is anticipated that patients will soon be able to engage with AI-based medical systems in a safe and convenient manner, thanks to the major advancements made by deep learning techniques. These intelligent systems will genuinely enhance patient care. Deep learning-based medical image analysis has several complications and difficulties, including small datasets. However, scientists are working hard to overcome these obstacles and use AI to enhance healthcare even more.

Table 1: AI-driven major biotech breakthroughs (2014-2025)

Year	Biotech- Innovation	Breakthroughs
2014	Deep learning	Drug screening and genomic pattern detection
2016	AI in gene editing	Safe and fast genomic engineering
2018	AI-based drug discovery	Drug discovery time reduced from years to months
2020	Covid-19 response	Protein structure prediction
2021	Alphafold-2	Protein engineering
2022	Protein designing	Vaccine and enzymes development
2023	Ai wet labs	Automated experiments robotically
2024	Multi-omics AI system	Précised medicines
2025	Bio-digital twins	Digital twins of human organs by AI

4. OBJECTIVES

This review's main goal is to inform readers about the developments, convergence, and integration of artificial intelligence. Additional goals include educating readers about artificial intelligence. • To explain the function of AI in the field of health - such as diagnosis of diseases (MRI, CT), Drug discovery and personalized treatment and prediction of early disease. • To talk about the effective use of AI in the healthcare sector such as personalized care of patient, and improvement in clinical trials. • To talk about the limitations of integrating biotechnology with AI such as the quality of data, high cost, a lack of skilled professionals and privacy concerns [10].

5. SIGNIFICANCE

By utilizing large data produced by contemporary high-throughput technologies and enormous databases, the combination of biotechnology and artificial intelligence (AI) has completely changed health management. By analyzing intricate datasets in proteomics, metabolomics, and genomes, AI technologies have greatly improved bioinformatics. AI has also revolutionized pharmaceutical biotechnology and vaccine production by anticipating immune responses and optimizing antigen selection, which has led to the quick development of potent vaccinations [11]. With cutting-edge approaches to diagnostics, individualized care, and therapeutic development catered to each patient's needs, this confluence holds revolutionary possibilities for the healthcare industry [12].

6. AI TECHNIQUES USED IN BIOTECHNOLOGY

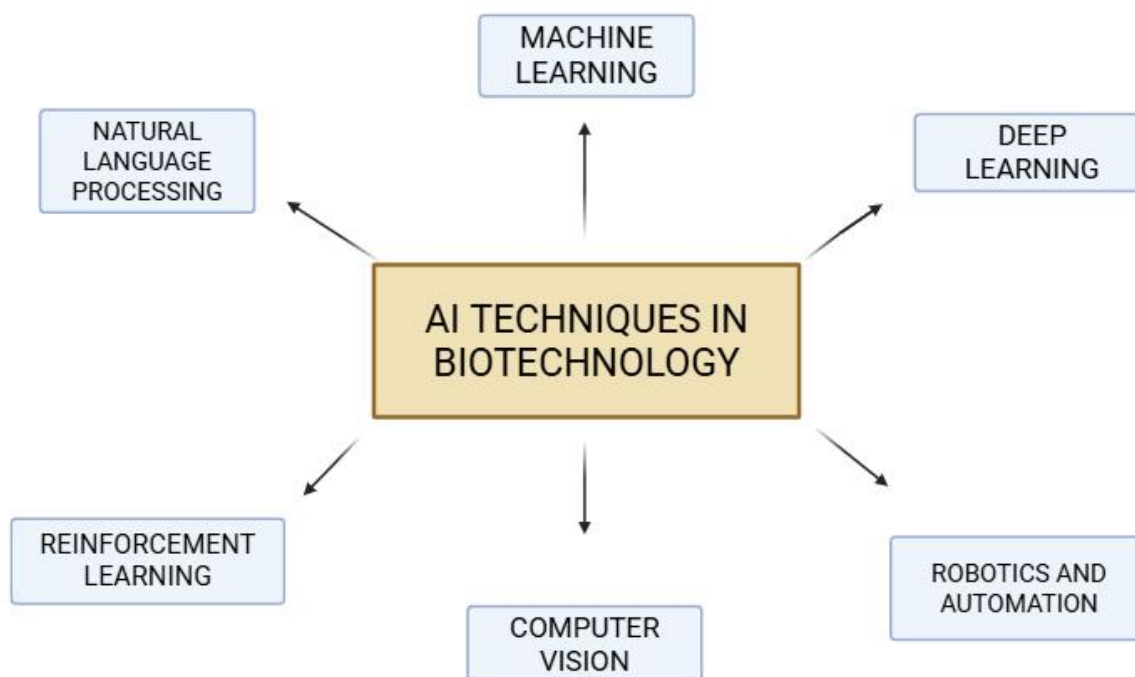


Fig. 1: AI Techniques used in Biotechnology

Research, development, and advanced diagnostics are being revolutionized by the use of diverse artificial intelligence approaches in biotechnology. They are as follows:

6.1 Machine Learning

ML is a branch of (AI), used to predict outcomes without relying on traditional manual methods in the lab by performing several permutations and combinations of data sets available for medicinal compounds to identify the optimal combination [13]. For biological data analysis, traditional model-based methods are still useful, but they can't make use of the vast amounts of data that are available, or even big data, to obtain insights, predict data behaviour, and understand complex relationships between collected data. Big data usage is becoming more and more significant in biotechnology and bioinformatics as it keeps expanding and becoming accessible for analysis by researchers globally [14].

6.2 Deep learning

Deep learning (DL) approaches emerged as a field of machine learning (ML) that is thought to be more successful and efficient when working with large volumes of data due to the vast generation of data, often known as the "big" data age. It has been demonstrated that these models can reach higher prediction accuracies than previously possible. When opposed to DL, ML's primary drawback is its inability to effectively handle natural data in its unprocessed state. Although DL models were first proposed in the 1980s, based on the perceptron model and the idea of neurons, they have only been regarded as state-of-the-art predictive models for large datasets in the last ten years [15]. For ex.- therapeutic discovery and development may be greatly aided by the precise identification of compound–protein interactions (CPIs) in silico, which could expand our knowledge of the fundamental mechanisms of therapeutic action. Latent characteristics from currently available large-scale unlabelled chemical and protein data are rarely used by conventional similarity- or docking-based computational approaches for predicting CPIs, and their application is frequently restricted to very small-scale datasets [16]. In order to reliably forecast CPIs on a broad scale, we present DeepCPI, a unique universal and scalable computational framework that combines potent deep learning techniques with efficient feature embedding and a representation learning methodology. DeepCPI uses a vast quantity of unlabeled data to automatically learn the low-dimensional, implicit, yet expressive characteristics of proteins and chemicals [17].

6.3 Natural language processing

Thanks to digitization, researchers today have unprecedented opportunities to compile a wide range of written information for examining simultaneous incidents. NLP, a technique that itself analyses and comprehends human language, permits scholars to simply pull useful insights from a written dataset without requiring costly computing work. NLP has advanced significantly in a few years due to the appearance of AI [18].

6.4 Reinforcement learning

A learning framework known as reinforcement learning (RL) employs interaction with an environment in which an agent sees its state in order to formulate a policy for a certain aim [19]. A learning framework known as reinforcement learning (RL) employs interaction with an environment in which an agent perceives the state of that environment to formulate a policy in terms of a predetermined goal. Its goal is simple: to make decisions and take actions that will optimize future benefits [20].

6.5 Computer vision

While AI techniques like neural nets have been widely utilized since the 1940s, computer vision approaches emerged in the late 1960s and early 1970s. Over the past few decades, computer vision has worked to develop several domains, including ML, virtual reality, augmented reality, computer graphics, and 3D reconstruction [21]. In 2010, computer vision was able to do sophisticated tasks such as robotic navigation, autonomous car navigation, object recognition, face detection, and fingerprint recognition [22]. For example, phenotyping facilitated by AI-enabled microscopy; ML, a branch of AI, has become a potent method in microscopy imaging. It makes it possible for biologists to more quickly, accurately, and consistently extract valuable information from tissue and cells. Without the need for specific instructions, machine learning (ML) makes use of algorithms that learn from the data to find patterns and features and provide predictions. Tasks like cell counting, phenotypic analysis, and noise correction—including fluorescent microscopy—all benefit greatly from machine learning [23].

6.6 Robotics and automation

Compared to the industrial robots that were initially developed fifty years ago to automate dirty, tedious, and dangerous tasks, today's medical and health-care robots are designed for entirely different environments and tasks—those that involve direct interaction with human users in the operating room and rehabilitation facility [24]. The commercial and scientific interest in medical and healthcare robots has grown significantly during the last ten years. Telerobotic equipment is now often used for surgery, which results in faster recovery times and more reliable outcomes in specific surgeries. The robotic system is enabling more intensive care that is continuously modified to meet the needs of the patient. [25].

AI-driven automated self-driving laboratory systems.

With the use of complex instruments and coordinated lines that integrate cutting-edge robotics and software with artificial intelligence capabilities, clinical laboratories are becoming more and more automated [26]. Robotic systems may now quickly and effectively complete tasks that were previously completed by technologists or lab assistants, thanks to automated technology. The testing volume can be significantly increased by using contemporary automated systems that handle sample storage all the way to assay analysis. However, automated laboratory testing system installation is extremely difficult, and optimal efficacy may not be attained unless the best implementation methodologies for these intricate systems are used [27].

7. Applications of AI in biotechnology

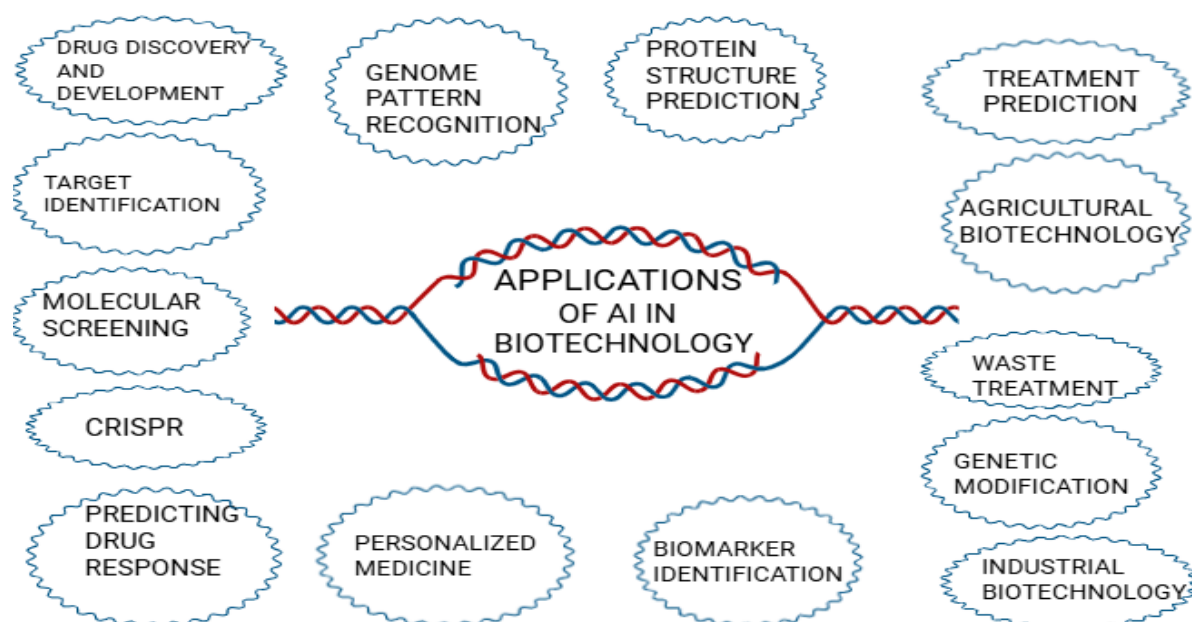


Fig. 2: Applications of AI in Biotechnology

7.1 Drug discovery and development

AI and biotechnology together have the potential to completely transform healthcare, especially in the area of drug creation. It is feasible to uncover new compounds, anticipate drug-target interactions, improve clinical trial candidates, and use machine learning methods [28]. This can reduce the time and cost needed to bring new medications to market and hasten the introduction of innovative treatments for a variety of illnesses. This is how artificial intelligence is transforming the labour-intensive and high-risk drug discovery process into one that is quick, simple, precise, data-driven, and likely to be successful.

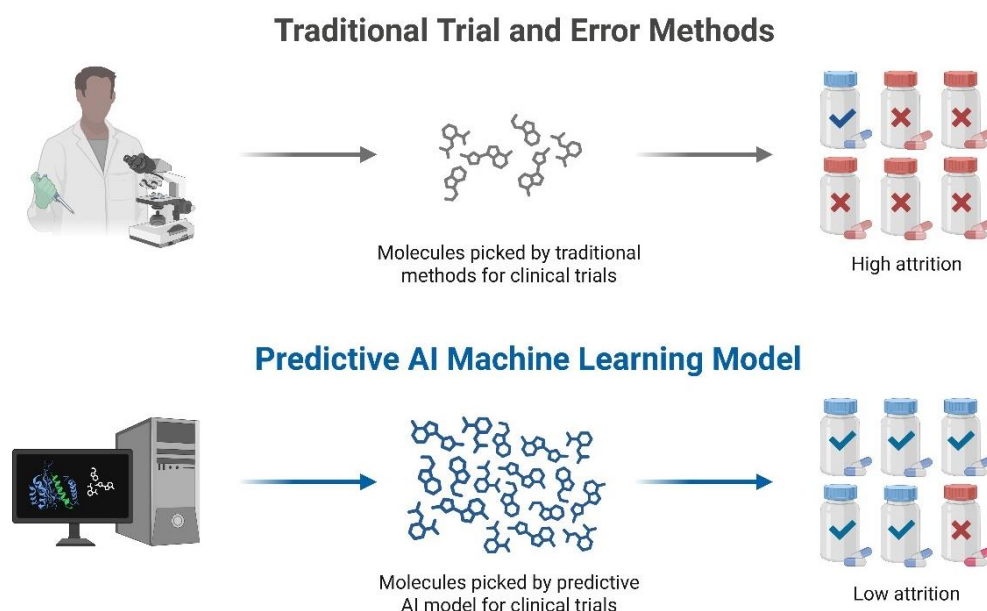


Fig. 3: Drug Discovery and Development (AI vs Traditional Techniques)

7.2 Target identification

Artificial intelligence using machine learning to find new anticancer targets. Applications of ML-based biological network analysis are used to examine vast amounts of complicated data in order to find trustworthy new targets that could be used to cure human

illnesses [29]. Classification, clustering, and neural networks are some of these ML-based biology analysis methods for finding new anticancer targets. [30].

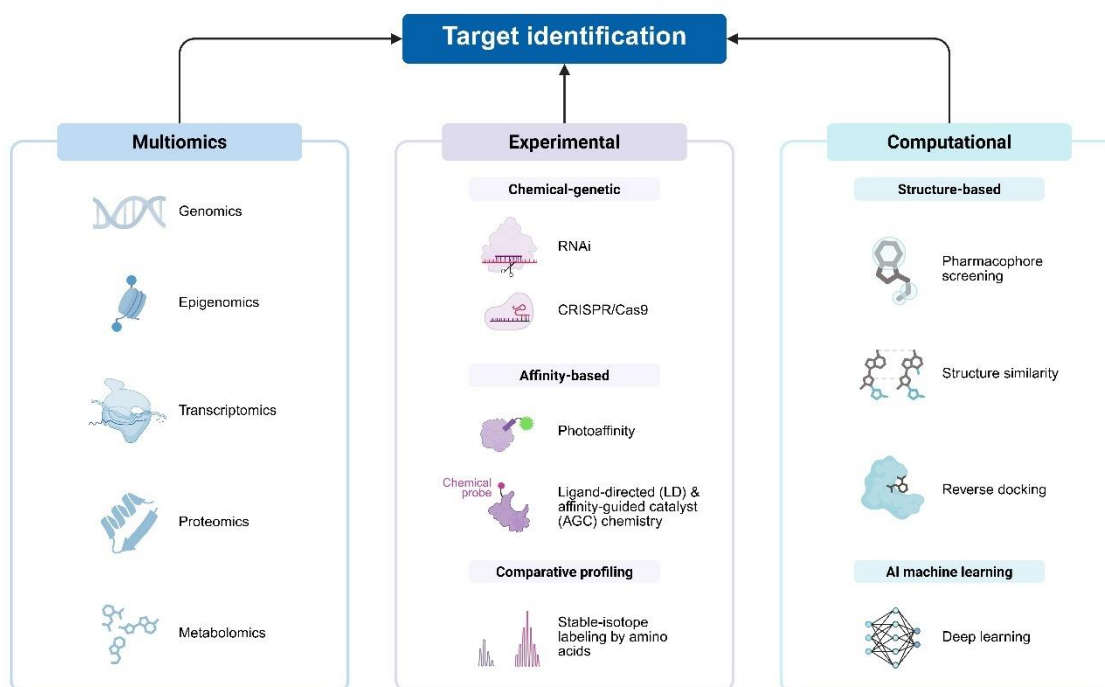


Fig. 4: AI-powered Therapeutic Target Discovery

7.3 Molecular screening

This technique has been used to identify TP53 changes in pathological tissue samples from primary head and neck cancer. A small percentage of cancer cells are discovered in histologically negative clinical specimens, including saliva, surgical margins, and chyle [31]. Accurately identifying these rare cancer cells in a range of clinical samples will have a major influence on otolaryngology, or head and neck surgery. This approach has the potential to screen for head and neck cancer and may require a revision of existing histopathologic staging utilizing cutting-edge molecular genetic techniques. [32].

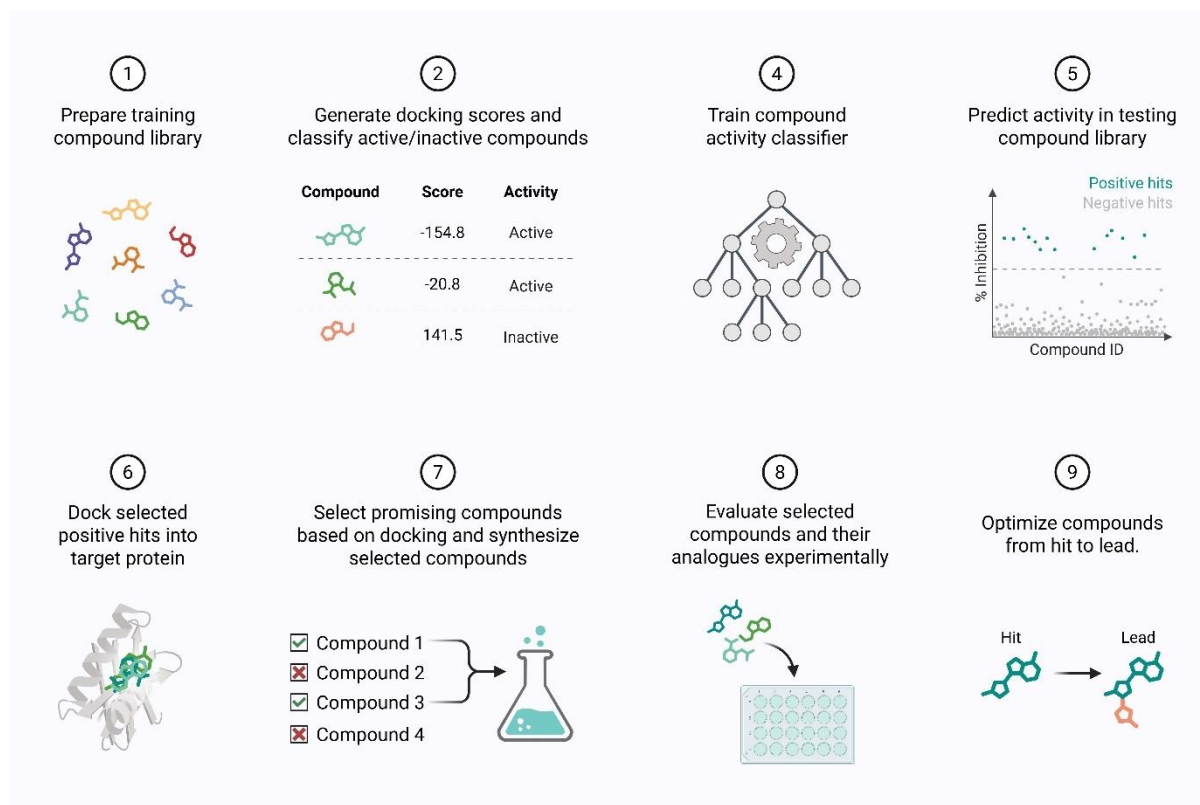


Fig. 5: Molecular Docking and Virtual Screening Workflow

7.4 Predicting Drug Response

Artificial intelligence (AI) systems are using an increasing quantity of preclinical data to develop and evaluate predictive models. Precision oncology and drug development are two scientific and therapeutic uses for these in silico models [33]. Here, we concentrate on predictive modelling of drug phenotypic activity in non-molecular targets, such as bacterial cultures or cancer cell lines, that serve as preclinical disease models. The AI subfield most commonly used to solve this significant healthcare issue is machine learning (ML), which includes DL [34].

7.5 CRISPR Design Optimization and Gene Editing Prediction:

Current evolution in gene editing, especially continuous development of CRISPR-Cas systems, has fundamentally changed experimental and applied procedures in medicine, and remedial design [35]. The specificity, rate, and explanatory power of genome-editing procedures have been enhanced more recently by the methodical application of AI and machine learning techniques. This has improved the prediction of aim effectiveness, assessment of non-target risks, and customization of chemical treatment designs. [36].

Applications of CRISPR/Cas9 for Genome Editing:

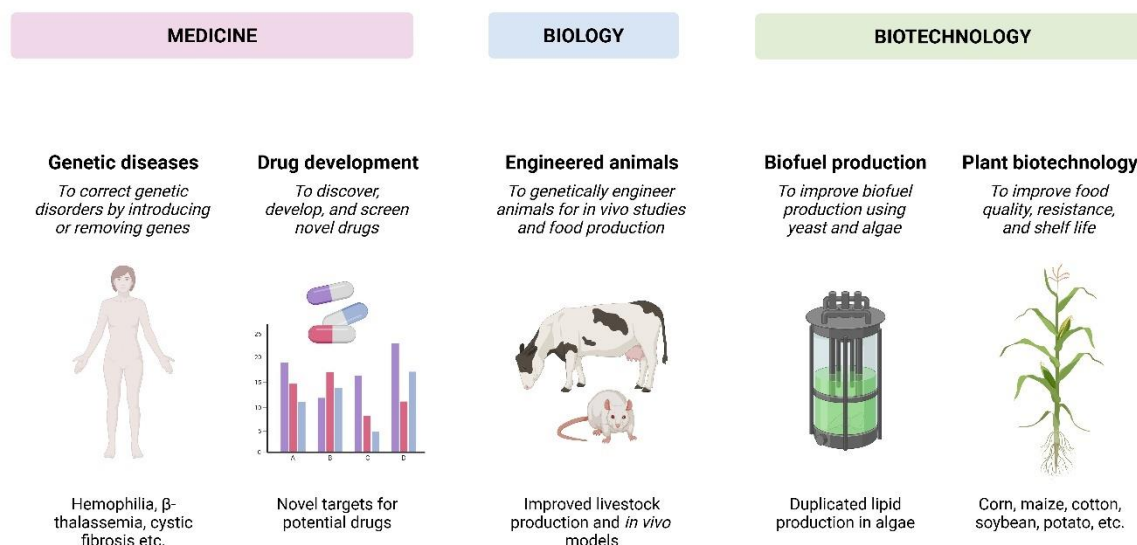


Fig. 6: Applications of CRISPR/Cas9 for Genome Editing

7.6 Genomic pattern recognition

An enormous amount of data has been produced by recent developments in molecular biology and genomic research, such as high-throughput sequencing techniques and cDNA microarray technology [37]. The Human Genome Project's completion, which sequenced the entire human genome, has also greatly increased researchers' desire to use this wealth of information in other scientific and medical domains. Effective computational processing of this enormous volume of data is quickly emerging as a significant challenge [38].

7.7 Protein structure prediction

Efficient computational methods must be developed to process these sequences as they are generated in order to analyze the information they carry. Finding the genes in freshly sequenced DNA is the initial step [39]. The GRAIL system, an integrated artificial intelligence system that combines parallel processing tools and multi-sensor neural networks to identify and understand genes in DNA sequences, serves as an example [40].

Computational biology workflow for the study of protein-protein complexes

In all docking approaches, the native complex is thought to be around the overall least of energy landscape composed of the collection of all complicated protein conformations that are conceivable in theory [41]. Any docking algorithm's primary difficulties can be broken down into three distinct categories: The first step is to list all of the potential docking orientations at a high enough resolution. Second, it is necessary to take into account the small or large structural alterations that take place throughout complex creation. Third, the near-native solutions must be chosen from among all potential alternatives. A scoring system that differentiates between native (-like) and non-native (-like) docking solutions is necessary for a trustworthy choice [42].

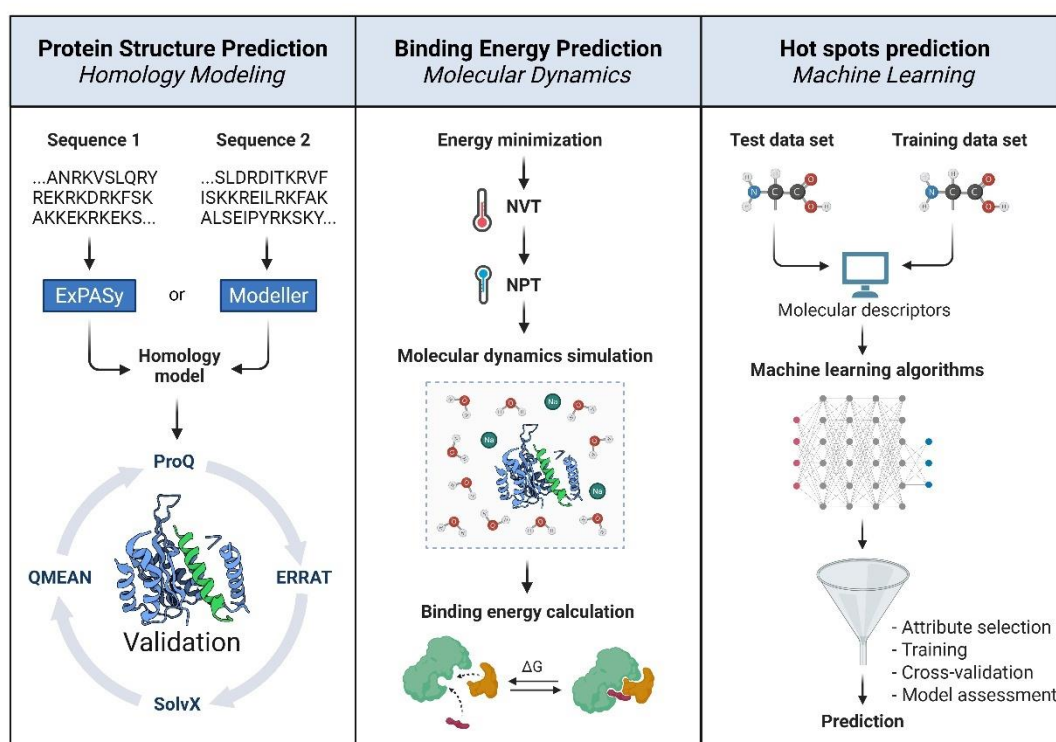


Fig. 7: Computational Biology Workflow for the Study of Protein-Protein Complexes

7.8 Personalized medicine

A novel approach to healthcare called "personalized medicine" entails simulating and modelling illnesses according to their underlying processes [43]. The paradigm of the 20th century, which defined disease by pathology or related signs and symptoms and conducted outcomes research based on the existence or absence of the disease syndrome, must be replaced by this approach. Massive volumes of precise data are made possible by new technologies like next-generation sequencing, the "omics," and powerful computers. Nevertheless, attempts to use these new technologies to comprehend complicated illnesses within the framework of the 20th century have not yielded the anticipated advancements in medicine [44].

It is necessary to illustrate the main benefits of the new framework and the shortcomings of the old framework in order to encourage doctors to adopt a paradigm shift. Given the simplicity of the pancreas as an organ for disease modelling and the substantial benefits of personalized treatment, chronic pancreatitis is a perfect complex ailment to examine in order to weigh the advantages and disadvantages of the two frameworks [45].

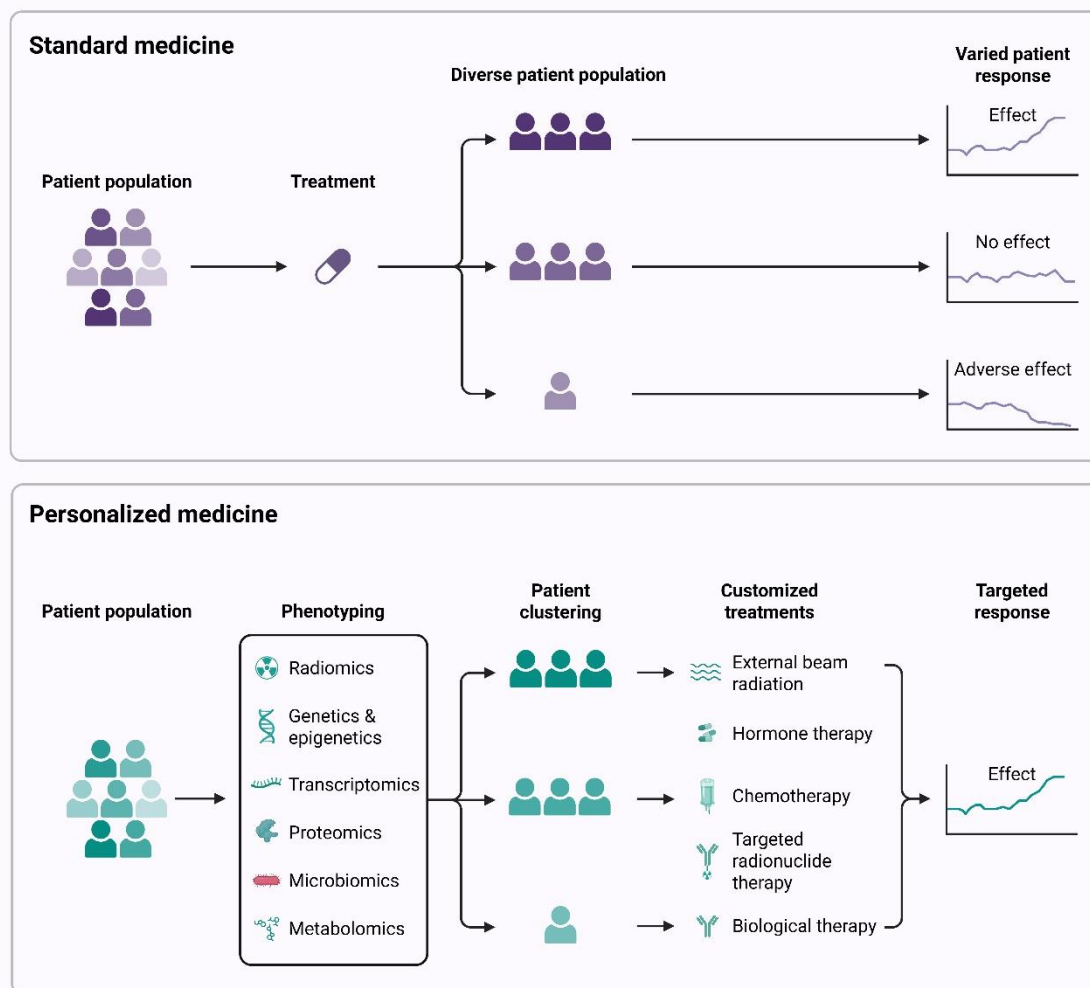


Fig. 8: Personalization of Medicine

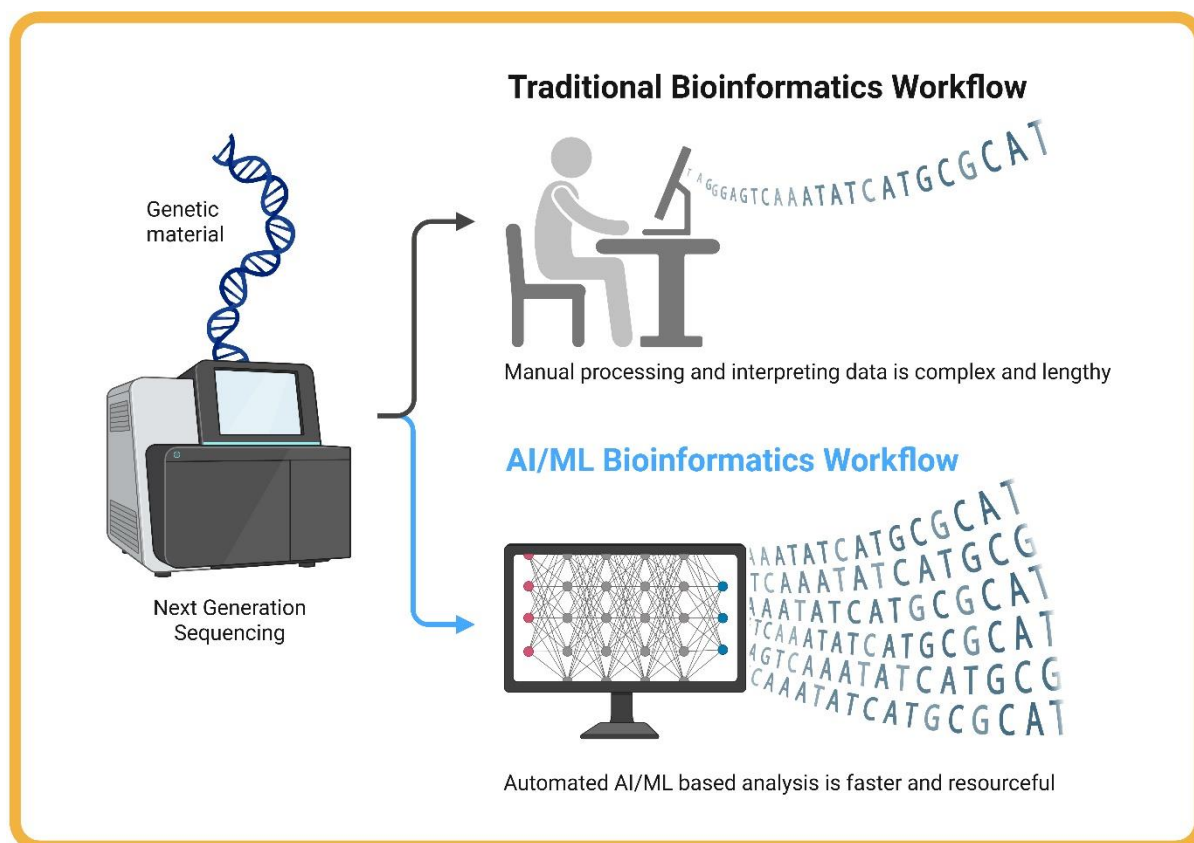
This image explains the process of personalized medicine.

It's a "ONE SIZE FITS ALL" model of individual unique characteristics of decision making and treatment.

The main aim is to produce targeted response in patient and also reduce risk of side and harmful effects [46].

7.9 Biomarker identification

By finding biomarker signals in large and varied datasets that are crucial for early disease identification and therapy, artificial intelligence (AI) in biomarker discovery enhances precision medicine. By spotting trends in enormous collection of and developing novel innovations that makes it viable to administer perfect and efficient therapies, AI technologies such as DL and ML diagnostics are transforming development of biomarkers [47]. Among the gaps that currently exist are those related to algorithmic openness, data quality, and privacy ethics. AI-powered biomarker discovery techniques aim to revolutionize cancer by increasing patient survival rates via more accurate early diagnosis and focused treatment [48].



The picture emphasizes how the AI/ML bioinformatics workflow is more efficient and uses fewer resources than the conventional approach. Although next-generation sequencing and the acquisition of genetic material are the first steps in both approaches, the analysis that follows differs greatly.

The conventional bioinformatics workflow is based on the laborious, time-consuming, and resource-intensive manual processing and analysis of data. It frequently finds it difficult to handle the enormous volume and complexity of contemporary genetic data.

7.10 Treatment prediction

Artificial intelligence has the capacity to enhance patient results and healthcare accuracy with the help of predicting and automating a number of cancers [49]. Risk assessment, early diagnosis, patient prognosis computation, and deep knowledge-based therapy selection are some of the uses of AI in oncology. A subfield of artificial intelligence called machine learning (ML) has shown great promise in predicting several types of cancer, including those of the breast, brain, lung, liver, and prostate [50]. ML allows computers to learn from training data. In fact, AI and ML have surpassed doctors in cancer prognosis. People with diseases other than cancer may also benefit from these technologies in terms of diagnosis, prognosis, and quality of life. Hence, it's essential for developing new projects that will benefit patients and progress current AI and ML technology. [51].

7.11 Agricultural biotechnology

Numerous significant uses of molecular biology and biotechnology exist to enhance crops, including as marker-assisted selection, plant in vitro propagation, micropropagation for embryo rescue, and specialist mutant breeding techniques such as focusing on locally caused lesions in genomes [52]. We concentrate on the subset of agricultural biotechnologies that use plant genetic engineering (GE), also known as the nonsexual transfer of foreign genes to enhance crops. This technology carries on the long-standing practice of combining agronomic techniques with genetic advancements to boost agricultural productivity [53].

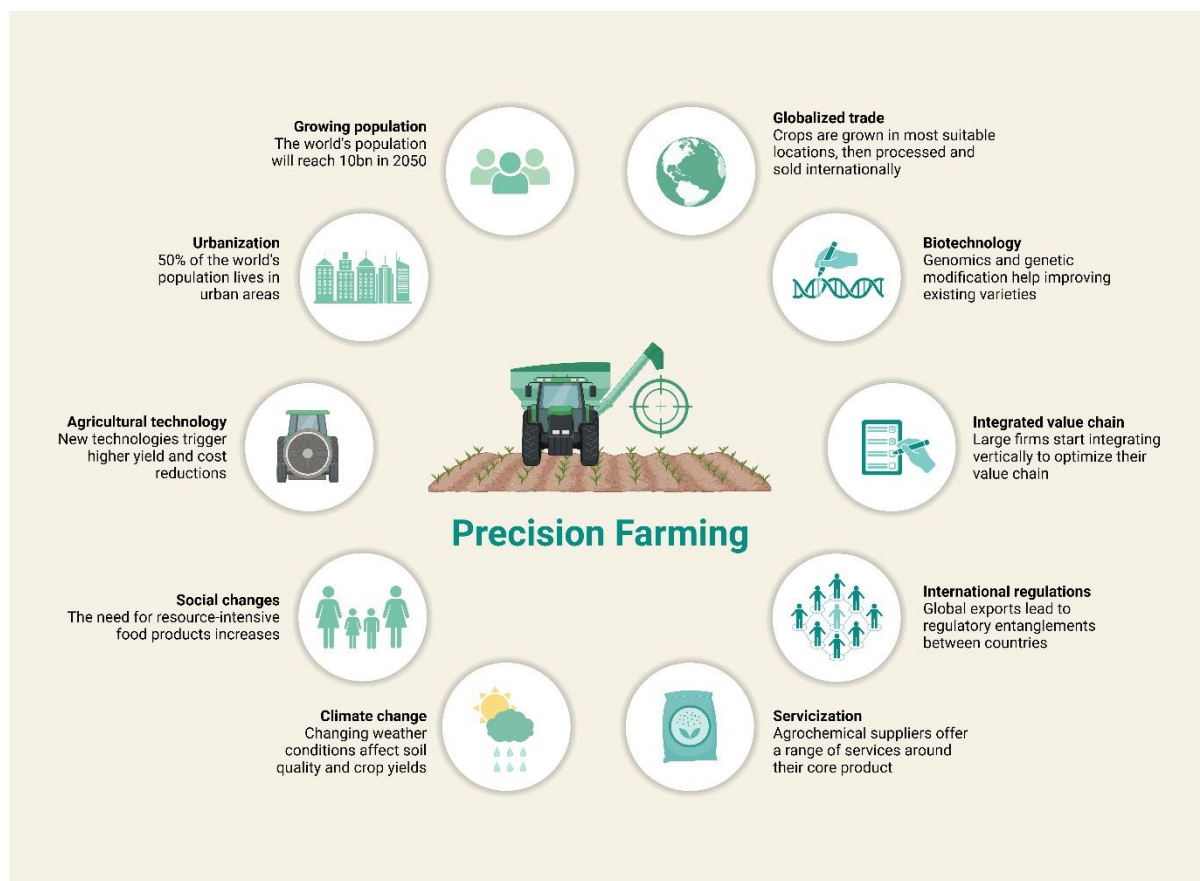


Fig. 9: Precision Farming

The picture is an infographic describing precision farming, a cutting-edge, technologically advanced approach to agricultural management such as site-specific management, Data driven decision, and resource efficiency. This strategy maximizes output, profitability, and environmental sustainability by observing, measuring, and responding to variability within fields using data and technology.

7.12 Industrial biotechnology

Industrial biotechnology, a third wave of biotechnology, is currently booming. Green biotechnology, which focuses on genetically modified crops, and red biotechnology, which targets the medical field, are distinct from industrial biotechnology, commonly known as white biotechnology [54]. Biological systems are used in industrial biotechnology to produce minerals, chemicals, and energy. Together with advances in molecular genetics, enzyme engineering, and metabolic engineering, this technology is primarily based on fermentation technology (the controlled use of microorganisms) and biocatalysis (the use of enzymes to catalyze chemical reactions). Recently, the phrase "white biotechnology," which refers to the beneficial environmental elements associated with the application of industrial biotechnology, was advocated by EU decision-making authorities and is currently gaining traction [55].

7.13 Waste treatment

Biotechnology applications in waste management strategies

Reuse and toxicity descriptions

The goal of analytical and biological approaches for toxicity characterisation is to specify what constitutes "toxic intoxicating amounts." Methodologies have advanced, yet there are still issues with how to interpret the data [56]. Toxicity has an impact on biological treatment plants and is a major factor in determining water quality-based criteria. In terms of sustainability, efficient analytical and biological techniques are essential for water reuse applications. Analytical assessments, research, and application—particularly with regard to process and system monitoring—remain largely unfinished. More advancements in this field are required [57].

Table 2: Various Roles of AI in Biotechnology

S. No.	AI Subfield / Technique	Biotechnology Applications	Precise Roles	Modern Tools / Examples
A	Machine Learning (ML)	Drug discovery, target identification, disease classification	Facilitates prediction of drug–target interactions Processes and interprets large-scale omics datasets Enables classification and clustering of disease-associated markers for improved diagnosis [58]	Random Forest, XGBoost, Graph Neural Networks (GNNs), DeepChem
1.	Supervised learning	Diagnosis of disease and drug discovery	training for neural networks and decision trees [59]	Programming libraries, pytorch
2.	Unsupervised learning	Anomaly detection	It can be used to investigate unknown or unprocessed data [60]	Clustering tools, t-SNE, UMAP
3.	Reinforcement learning	Robotics, adaptive prosthetics	The objective is only to make choices that will maximize future rewards to the greatest extent feasible. [61]	Q – learning, SARSA
4.	Deep learning	MRI, X-rays and tumor detection	Facilitates new drug discovery and prediction of patient outcomes [62]	Artificial neural network, RNN, CNN LSTM
5.	Transfer learning	Tumor detection, medical imaging	particularly in the domains of multiple language text classification, sentiment classification, text classification, and spam email detection.[63]	MobileNet and Fast AI
6.	Semi supervised learning	PET scans, classification of diabetic retinopathy	classification problem, the class is provided as a categorical label, and the data element to be classified is represented as a feature vector.[64]	Generative models, graph-based SSL models
7.	Active learning	Drug development and drug discovery	Annotation of genome and protein function [65]	Pytorch and keras
8.	Ensemble learning	Virtual screening and drug discovery	Combine random forest, svm and neural networks [66]	Pytorch and tensorflow
9.	Federated learning	AI model training across multiple institutions.	arises as a paradigm that solves this problem by allowing institutions located in different	TFF PySyft

			places to work together on a model training procedure. [67]	flwr
10.	Few shoot learning	Drug discovery and plant pathology	a remedy for the lack of data that has prevented deep learning from being used [68]	JAX PyTorch
B	Neural network architectures	Bioinformatics, Gene prediction, cancer identification	powerful as nonlinear signal processors, but obtained results are often far from satisfactory [69]	TensorFlow, Keras
11	Convolutional neural networks	Drug discovery, genomics	most important networks in domain of deep learning. attained extraordinary progress in a variety of fields, such as natural language processing and computer vision.[70]	Deep learning, caffe, keras
12	Recurrent neural networks	GENE expression, EHR data	extensively used in fields of study that deal with sequential data, including text, audio, and video [71]	LSTM, GRU
13	Long term short memory networks	ANALYZE, biomaterial degradation	transformed deep learning, especially for applications requiring sequential data modelling.[72]	MATLAB PyTORCH TENSORFLOW
14	transformers	Protein engineering, Mutation effects	influencing the Natural Language Processing (NLP) sector. There are pertinent similarities between natural languages and biological sequences. [73]	Multihead attention, Positional encoding
15	autoencoders	Drug discovery	an <u>unsupervised learning</u> model. act as a dimensionality reduction method [74]	Adam, Dense, Conv2D
16	Variational autoencoders	Multi-omics data integration	They are constructed using neural networks, which are typical function approximators. [75]	PyTORCH TENSORFLOW
17	Graph neural network	Virtual screening, Protein-protein interaction prediction	capture a graph's reliance by sending messages between its nodes. [76]	pyG DGL
18	Generative adversarial networks	Drug discovery	presenting remarkable outcomes on image segmentation [77]	PyTORCH TENSORFLOW

19	Multilayer perceptrons	Predictive modelling, classification	Within the network, signals are only sent in one direction: from input to output.[78]	Keras Scikit learn
20	Neural ordinary differential equations	Simulate and predict behavior of complex	attracting increasing attention in various research domains recently. [79]	ODE solvers JAX JULIA
C	Statistical and predictive modelling	Accelerate drug discovery	allow for the prediction of specific facets of human behaviour, including objectives, behaviours, and preferences [80]	Python SAS IBM SPSS
21	Bayesian network	Disease diagnosis and drug discovery	integrate various problems and system elements; make use of data from various sources; and deal with uncertainty and missing data [81]	OpenBUGS python
22	Hidden markov models	Gene prediction, MSA	The development of hidden Markov model (HMM) techniques has given profile analysis a stronger mathematical foundation. [82]	SAM HMMER
23	Markov chain monte carlo	DRUG development, Protein structure function	MCMC method is a statistical tool that requires a lot of computing power. [83]	Stan BUGS
24	Logistic regression models	Biomarker detection, Clinical diagnosis	elucidate the connection between an independent variable and a qualitative dependent variable. [84]	Python SPSS
25	Survival analysis models	Clinical trials Bio-manufacturing	capacity to deal with censored observations that are disregarded by techniques like linear regression and a t-test (or analysis of variance) for comparing the survival periods of two or more groups [85]	KAPLAN-Meier Log-rank test
26	Sequence alignment algorithms	To identify similarity between DNA, RNA	Numerous other tasks, such as phylogenetic analysis is guided by it. [86]	BLAST FASTA
27	Protein structure prediction models	RATIONAL DRUG DESIGN, DIAGNOSIS	Protein structure prediction, which is mostly based on sequence and structure homology, has grown in significance. [87]	AlphaFold RoseTTAFold

28	Genome annotation models	Accelerated genomic discovery	The annotation is what connects the sequence to the organism's biology. [88]	MAKER AUGUSTUS
29	Metagenomic classification models	Novel enzyme screening, Targeted enzyme discovery	allowed for the direct extraction, sequencing, and study of particular phylogenetic marker genes or the complete genomic content of microbial communities, allowing researchers to get over this restriction. [89]	MEGAHIT
30	Phylogenetic machine learning	Construction of phylogenetic tree	Tree topologies and branch lengths have been inferred, substitution models have been chosen, and introgression and diversification have been inferred downstream using methods based on simulated training data. [90]	EBG PHYDDLE
E	Computational biology models	Synthetic biotic models	Through theoretical investigation and practical modelling, computational biology provides a strong foundation for tackling important scientific problems. [91]	PYTHON GROMACS
31	Systems biology modelling	Metabolic engineering, Drug discovery	seeks to forecast biological systems' behaviour based on the collection of molecules involved. [92]	COPASI V-CELL
32	Gene regulatory network prediction	Methodology	includes signal transduction, metabolism, cell cycle, and cell differentiation [93]	SCODE SCENIC
33	Protein protein interaction prediction	Drug discovery Target therapeutics	have attracted interest in computer-aided drug development and bioinformatics. [94]	GNN ALPHA-FOLD HADDOCK
34	Molecular docking AI models	Accelerated virtual screening De novo drug design	The underlying mechanism and the detailed process of molecular docking are both clear and comprehensible. [95]	ATOMNET AUTODOCK- VINA
35	Drug target interaction prediction	Drug discovery Drug repurposing	to make large-scale predictions about possible drug-target interactions. [96]	DEEPCCREEN, DRUGBANK

F	Data driven optimization techniques	Bioprocess development, Strain engineering	However, such objective functions might not exist in many real-world optimization issues. [97]	PYTHON SQL EXCEL
36	Evolutionary algorithms	Metabolic engineering, Protein and molecular design	This article compares three probabilistic optimization techniques based on the notion of natural evolution: GA, EP, and (ESs).[98]	GA GP DE
37	Genetic algorithms	Bioinformatics Protein structure prediction	methods that can be used for a variety of optimization issues. They are appealing for numerous optimization issues in practice because of their adaptability.[99]	DEAP MATLAB LEAP
38	Particle swarm optimization	Drug design Protein structure prediction	An algorithm for population-based stochastic optimization inspired by the clever collective behavior of certain animals, such schools of fish or flocks of birds [100]	MATLAB
39	Stimulated annealing	Protein folding Bioprocess optimization	for determining a cost function's global minimum when it may have multiple local minima [101]	MATLAB AUTODOCK
40	Bayesian optimization	Bioprocess engineering Protein engineering and design	A method for optimizing objective functions that need a lot of time (minutes or hours) to assess [102]	BOTORCH GPyOPT
G	Image & Signal Analysis in Biotech	Microscopy, Imaging spectroscopy	Research and development use a variety of imaging devices. Automated image analysis enables quick, precise, and trustworthy quantitative analysis when compared to human-performed manual approaches.[103]	MATLAB DEEP LEARNING
41	Medical Image Analysis	Drug discovery Tissue engineering	is crucial to make use of this growing volume of data and to examine and display the information it contains in a manner appropriate for the particular medical purpose.[104]	3D SLICER ITK-SNAP
42	Biomedical Signal Processing	Cross data learning, Robust handling	entails recognizing patterns, compressing or expanding into higher or lower dimensions, extracting linear and non-	MATLAB LABVIEW BIOSIG

			linear features, and identifying signal behaviour.[105]	
43	Cell counting & Imaging Automation	Bioprocess and biopharmaceuticals	has a significant impact on drug development, toxicity, and standard cell culture. [106]	BIORAD DENOVI
44	Microscopy Image segmentation	Disease diagnosis, Biofilm study	has a significant impact on computer-aided diagnosis and prognosis. Numerous facets of clinical practice and medical research have benefited from machine learning approaches. [107]	CELL POSE MIB
45	Digital Pathology AI	Drug discovery and development	plays a vital part in the scientific laboratory setting and is becoming more and more technologically necessary. [108]	IMS HALO QUPATH
H	Natural Language Processing	Genomics and bioinformatics	The goal of NLP is to perform this task as accurately and successfully as a human would (for a limited amount of text). [109]	NLTK CLOUD NLP GENSIM
46	Biomedical Text Mining	Target identification and validation, Genotype and phenotype mapping	High-throughput and computationally automated. However, because natural language processing is so complicated, it is prone to errors.[110]	BIOBERT PUBTATOR
47	Named Entity Recognition for Biological Terms	Gene/protein identification, Disease mapping	a sub-task of IE which finds and classifies the names/entities. [111]	ML BERT CRF
48	Literature Based Discovery Systems	Target identification And natural product research	The reader is introduced to important system components, evaluation techniques, contemporary trends, and both historical and contemporary LBD models. [112]	METAMAP UMLS MEDLINE
49	Knowledge Graphs in Biology	Target identification and validation, Precision medicine	Knowledge graphs have become popular techniques for generating hypotheses and storing data. [113]	KG-HUB BIOCYPHER PETAGRAPH
50	AI-powered Laboratory Automation	High throughput screening, Bioprocess fermentation and optimization.	have brought about the digital revolution of numerous diagnostic methods and enhanced the promptness and precision of diagnosis. [114]	AI- ASSISTATNT, AUTOMATED ROBOTICPLATFORM

8. ETHICAL CONSIDERATION

Although there are numerous useful applications of AI and biotechnology in healthcare, there are also significant ethical issues and challenges. There are significant ethical questions raised by the unequal distribution of AI-driven healthcare solutions, which may worsen health disparities. Preventing the expansion of health disparities and ensuring that the benefits of contemporary technologies are distributed equitably among all populations is imperative. [115].

9. TRENDS IN ARTIFICIAL INTELLIGENCE

Trends in AI-biotech start-ups and industry investment: Biotechnology could undergo a radical transformation thanks to blockchain, the Internet, and artificial intelligence. AI-based algorithms help biotech companies in increasing quality control, optimizing operations, and streamlining manufacturing. Through predictive analytics and real-time data collection from sensors and equipment, AI can facilitate proactive maintenance of IoT devices, minimizing downtime and increasing productivity. Blockchain technology may help improve supply chain transparency in terms of security and traceability, safeguarding biotech products or resources. Consequently, the biotech production industry will benefit from these three factors in terms of innovation, efficiency, and reliability. AI is essential for customized medications [116].

11. AI IN DIAGNOSIS

Healthcare practitioners can identify and diagnose a range of conditions by using AI algorithms to examine medical images from DXA, CT scan, MRI, and ultrasound. AI methods including fuzzy logic, recurrent neural networks (RNNs), logistic regression (LR), and artificial neural networks (ANNs) have been used to detect difficult medical issues with high precision levels. TB, high blood pressure, stroke, brain disease, dermatosis, and harmful illnesses are notable examples of these. Additionally, AI algorithms have shown remarkable efficacy in improving patient outcomes, lowering the financial burden of malignant diseases on the healthcare system, and detecting various malignancies in their initial development, like liver carcinoma. A 2020 study by Chen et al.⁷ that looked into the use of ANNs in the diagnosis of liver illness demonstrated exceptional accuracy of diagnosis.

The introduction of AI in the 1950s revolutionized the healthcare sector by fusing machine learning and precision medicine to alter treatment planning, medical imaging, and diagnostic processes. From its early information-based system that depended on therapeutic data and guidelines to more recent Artificial intelligence platforms that employ artificial neural networks (ANNs) and statistical methods for disease identification and treatment, artificial intelligence in healthcare has changed throughout time [117].

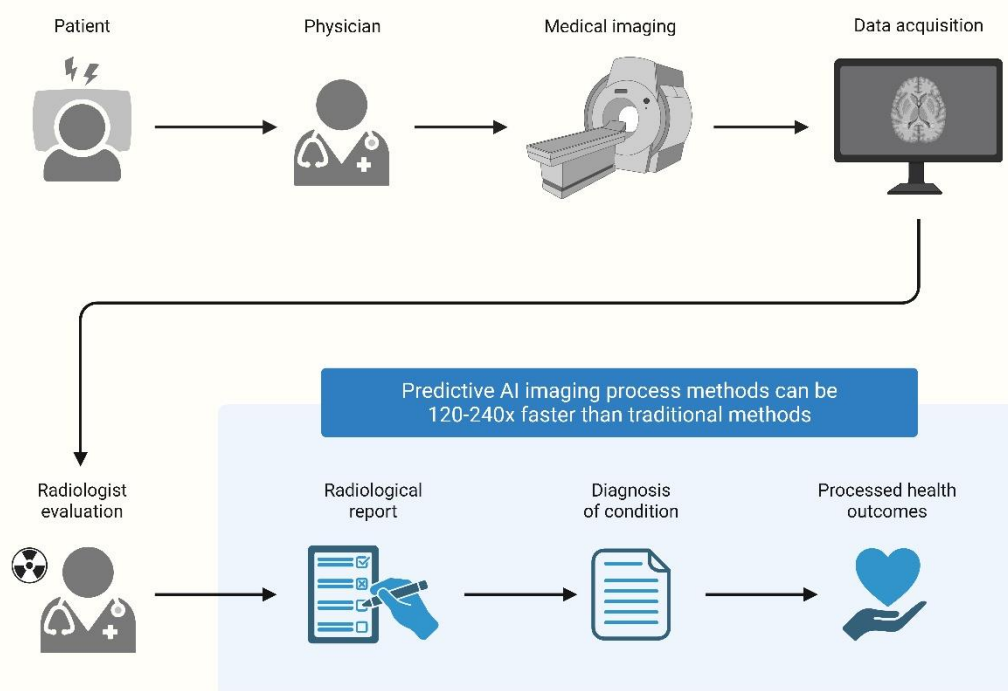


Fig. 10: Biomedical Image Analysis (AI vs Traditional Techniques)

The above image is a flowchart that describes the steps involved in Biomedical Image Analysis, emphasising the benefits and distinctions between applying artificial intelligence (AI) and more conventional methods. Predictive AI imaging techniques can be far quicker and more accurate than conventional, human-reliant techniques, as the graphic highlights. It also shows how patient data is collected, processed, and examined for diagnosis. Various technologies such as Deep learning (DL), Machine learning (ML), and data analyses are used to study different diseases. AI have transformed the way of diagnosis of critical conditions such as heart disease, brain disease, cancers, nervous system disorders and immune system disorders. Although AI cannot replace medical professionals, it acts as a powerful tool that supports medical professionals. Here are some specific diseases that can be diagnosed by AI faster as compared to conventional methods.

A. Cancer: It is one of the most dangerous and widely spread disease around the world with the greatest number of deaths. In this disease, cancerous cells replicate in our body, leading to the death of normal cells. Early detection is mandatory in case of cancer. For instance, AI helps in fast and precise diagnosis of breast, lung, skin (melanoma), colon, and prostate cancer. Medical imaging (MRI, CT, PET, and histopathology slides) is analysed by AI models (such as Deep Learning CNNs). AI uses genetic data to discover mutations, categorize tumor stages, and detect tumor borders. By predicting which medications will be effective based on a patient's genetic profile, AI aids in precision oncology. Tools such as Google DeepMind's use advanced AI for breast cancer screening, which outperforms radiologists in accuracy.

B. Heart conditions (CVDs): All over the world, millions of people are affected by CVDs. In this condition, blood vessels and the heart are affected, which leads to heart attacks. It reduces the heart's ability to pump and blood flow is affected. In this case, it is necessary to detect and diagnose minor and critical symptoms. Diseases such as Heart Attack, Coronary Artery Disease, Arrhythmia are diagnosed by AI and tools. AI-based ECG analysis identifies blockage patterns, heart failure concerns, and abnormal heart rhythms. It uses lifestyle information, blood test results, and patient vitals to predict the likelihood of a heart attack. Tools such as IBM Watson Health, which predict cardiac risk using AI.

C. Hereditary Conditions: It is a disorder that is transferred from parents to children and affects their genes too. It can occur due to gene mutation, abnormality or chromosomal disorder. Symptoms can be weakness, fatigue, abnormal growth, organ dysfunction etc. It includes Huntington's disease, Cystic Fibrosis, and Down syndrome. To find gene mutations connected to hereditary disorders, AI systems examine genomic sequences. Deep learning algorithms expedite the interpretation of next-generation sequencing (NGS) data and identify uncommon genomic variations. Tools used such as Google's Deep Variant accurately identify genomic variations.

D. Nervous System Disorder: The condition in which spinal cord and brain is affected. Nervous system controls various functions like thinking, sensation, coordination etc. if it is damaged, there will be disturbance between brain and body. This disorder includes stroke, epilepsy, Parkinson's disease, and Alzheimer's disease. Here, AI examines MRI and PET scans of the brain to find early structural or metabolic alterations. To predict Alzheimer's disease early, machine learning models monitor speech patterns, locomotion, and cognitive deterioration. Tools used: MRI-based AI is used by IBM Watson and Neuro Predict to detect Alzheimer's disease.

E. Immune System Disorders: Immunity is the ability of our body to fight against various foreign diseases. The immune system helps in preventing our body from those diseases and helps us attain a healthy lifestyle. If there is a lack of immunity, it can lead to any immune disorder or may be an autoimmune disease. This disorder slowly affects our own immune system and shows major symptoms. It is essential to diagnose and detect those symptoms as soon as possible. AI helps in the detection of any kind of autoimmune disorder.

It includes multiple sclerosis, lupus, and rheumatoid arthritis. AI uses omics data (transcriptomics, proteomics) to identify biomarkers. Microsoft's AI for MS progression analysis is an example tool.

S.NO.	DISEASE	TRADITIONAL METHODS	AI/BIOTECH BASED TREATMENT	LIMITATIONS
1.	Cancer	Chemotherapy, surgery	MRI, CT, DeepMind	High cost, data privacy
2.	CVD	Medication, surgery	AI-Based ECG analysis	Limited availability and a highly affected population

3.	Hereditary conditions	Physical or occupational therapies, surgery	Genomic sequence examination through AI	Data security, black box problem
4.	Nervous system disorders	Medication therapies, surgeries	Machine learning models for the prediction of early Alzheimer's disease	Lack of transparency, data privacy
5.	Immune system disorders	Stem cell transplantation, surgery	AI use omics data to identify biomarkers	Data availability, clinical and ethical challenges
6.	Liver failure	Medication, supportive care	Additionally, MLAs are starting to be used as instruments for LT recipient screening and selection as well as for posttransplant outcome prediction.	Biased and incomplete datasets, data standardization.
7.	COVID-19 diagnosis and tracing	Viral test, PCR test, antigen test	ANN (Artificial Neural Networks) helps trace and diagnosing symptoms of COVID-19 in 5 layers	Data privacy and interpretability.

12. AI-POWERED PERSONALIZED MEDICINE

Precision medicine, often known as personalized medicine, is an alternative method of managing diseases that is adapted to the unique needs of each patient. Conventional medicine usually employs a one-size-fits-all treatment strategy, which could overlook individual differences in lifestyle, environment, and genetics that are crucial in determining treatment response and disease susceptibility. Deep neural networks, big data analytics, ML, and AI in medical care are exciting medical topics that may result in patient-specific therapy regimens and predictive diagnostic techniques. Another remarkable accomplishment is the incorporation of artificial intelligence in the medical field, with the main benefactors being cardiology, cancer, and dermatology. For instance, 5.4 million Americans with skin cancer each year were able to classify many forms of the condition at a level comparable to a clinician using deep neural networks. Similarly, 30 million US adults with cardiac conditions may benefit from the application of AI-powered techniques in cardiology for risk assessment and diagnosis [118].

CONCLUSION

The integration of AI and biotechnology represents a pivotal advancement in life sciences, enabling researchers and practitioners to uncover insights from complex biological data with unprecedented speed and accuracy. AI-driven tools and techniques have enhanced various biotechnological domains, including genomics, drug development, diagnostics, and agricultural biotechnology. These technologies not only streamline research processes but also contribute to more precise, personalized, and predictive approaches in healthcare and industrial biotechnology. Despite its enormous promise, issues like data privacy, algorithm transparency, and the requirement for interdisciplinary cooperation must be resolved in order to fully reap the rewards of AI. The future of biotechnology will be redefined, innovation will be accelerated, and results will be improved as both sectors continue to develop.

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