Artificial Intelligence in Biology

Anurag[1], Yashdeep Srivastava[2], Aniket Sharma[3], Dheerendra Kumar[4], Sumit Pandey[5], Nishchal Maurya[6], Abhishek Gupta[7]

[1,3]Student, Department of Biotechnology, R. R. Institute of Modern Technology
[2,4,5,6,7]Faculty, Department of Biotechnology, R. R. Institute of Modern Technology

Abstract:
This article provides an in-depth analysis of the use of Artificial Intelligence (AI) in various aspects of biology, including healthcare, agriculture, and environmental monitoring. It highlights AI's ability to mimic human intelligence and analyze large datasets for predictions and tasks. The article also discusses its integration into Chinese medicine, where AI-guided diagnostic and therapeutic systems optimize clinical treatments and health management. AI is also used in disease management, analyzing data on diseases and pests, predicting their impact on ecosystems, and implementing preventative measures. The article also highlights the role of integrated information systems in environmental monitoring.
Artificial intelligence (AI) has significant potential in healthcare research and chemical discoveries. Pharmaceutical companies are using AI to improve drug development by utilizing computational biology and machine learning systems to predict molecular behavior and the likelihood of finding a useful drug. This saves time and money on unnecessary tests. Clinical studies, electronic medical records, high-resolution medical images, and genomic profiles can be used as resources for drug development. Strong AI systems can analyze extensive data sets in pharmaceutical and medical research. This review focuses on integrating knowledge of cancer drugs, drug resistance, next-generation sequencing, genetic variants, and structural biology in cancer precision drug discovery.

Keywords: AI in biosciences, biomedical, Agricultural engineering, Drug discovery, Molecular Diagnostics

(A) Introduction to Artificial Intelligence in Biology:

1. Overview of AI and its Applications:

Artificial intelligence (AI) is a subfield of computer science that aims to mimic human intelligence and perform tasks similar to human abilities. It is closely related to data science, machine learning, and statistics. Artificial intelligence (AI) is the technical simulation of human intelligence using computer-based programs and robotics to mimic biological thought processes and physical expressions [1]. It involves interdisciplinary application-oriented toolboxes such as machine learning, deep learning, robotics, gesture, facial expression, and cognitive and language processing. AI was first formally defined at the Dartmouth Summer Research Project workshop in 1956 and later developed by Stanford University in 1972. AI's promise lies in its ability to discover structure in large datasets and use this structure to make predictions or perform tasks. Its strengths complement human abilities, such as the ability to see patterns in high-dimensional data. Modern AI systems rely on variations of artificial neural networks (ANNs), inspired by the organization of the nervous system. There are three classic paradigms in AI for extracting structure from data: supervised learning, which predicts the labels of novel items, and unsupervised learning, which has recently leap-frogged all previous algorithms in competition. More breakthroughs in AI are expected in the coming years, in various domains. AI systems have the ability to see patterns in high-dimensional data and serve as powerful tools to assist researchers rather than replace them.

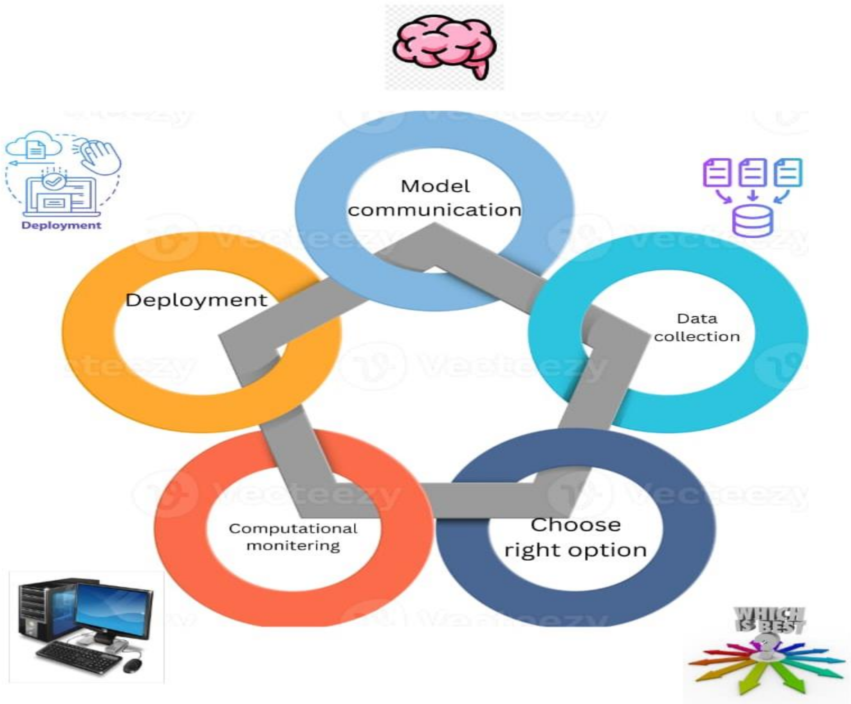
Artificial intelligence (AI) is a complex concept, with its definition largely based on Alan Turing's Turing test. AI refers to a machine's ability to communicate, reason, and operate independently in both familiar and novel scenarios, similar to a human. However, this is far beyond the scope of current methods and is not commonly used. AI is often used interchangeably with machine learning or deep learning, a specific form of machine learning that involves algorithms and statistical models learning from labelled training data to recognize and infer patterns. This makes AI a complex and challenging concept to define precisely.

I. Artificial Intelligence and Chinese Medicine:

AI technology has been applied extensively in healthcare, including robotics-mediated complex surgical procedures, high-throughput clinical diagnosis and therapy, telemedicine, and universal coding systems for healthcare-associated information exchange (Fig 1). In the 1970s and 1980s, Chinese scholars combined AI technologies with traditional Chinese medicine (TCM) for the first time, developing an AI-guided assistive diagnostic and therapeutic system. AI technology has been helpful in optimizing and objectifying four diagnostic methods to provide more efficient clinical treatments and standardized health management [2]. Despite rapid technological advances, there has been less interest in modernizing TCM diagnosis and therapy with AI-guided skills. In the era of next-generation technological breakthroughs, it is crucial to blend AI skills with TCM-based treatment strategies to make them accessible, reliable, and affordable for all people.

Artificial intelligence is a branch of computer science that simulates intelligent behavior in computers using algorithms established by humans or learned through computer methods. Machine learning is a subfield of AI that improves performance by continuously incorporating new data into an existing model. Deep learning (DL) is a subfield of ML that uses mathematical algorithms deployed on multi-layered computational units, such as neural networks with different architectures, to simulate human cognition. Artificial neural networks, with their different architectures, can effectively analyze unstructured data, a common type of medical data. These unstructured data, often acquired through patient-provider interactions or imaging, can be processed using natural language processing (NLP) techniques and recurrent neural networks. Convolutional neural networks are the most promising AI architectures for exploring imaging files, despite their potential in other data types. Machine learning (ML) models are developed and validated through various steps, including problem identification, data collection, pre-processing, training, internal validation, testing, optimization, evaluation, and external validation[3]. These steps are crucial for creating reliable models that can be applied in clinical practice. After deployment, results and application should be monitored for drift checking to ensure model consistency. Clinical utility of ML models must be assessed using specific metrics, such as the receiver operating characteristic curve (ROC curve) and confusion matrix, which plot the true positive rate and false positive rate, and the accuracy level.

Figure 1: Artificial Intelligence Flywheel: Graphic representation of the artificial Intelligence and data cycle for building effective and responsible machine learning models for healthcare.



II. AI tools for analyzing and interpreting data:

AI has revolutionized the way we analyze and interpret data, with applications in various fields such as neuroscience, protein modeling, genetic sequence analysis, medical diagnosis, and drug discovery [4]. The recent success of deep learning has rekindled interest in these approaches, with researchers engineering artificial neural networks (ANNs) that can fulfill their potential.

The last decade has seen significant advances in the ability of AI to solve difficult problems once thought intractable for artificial systems. Neuroscientists have also begun using ANNs as models of real neural computation, with new experimental techniques facilitating direct comparisons between ANNs and real brains. This correspondence has been observed in feedforward and recurrent neural networks across various brain areas, including visual, language, motor, and prefrontal areas.

For example, the inferotemporal cortex, a critical region for representing object identity in primates, is spatially organized into a map of object space whose two axes are the same as those in a late layer of the deep network trained on object classification. Computational neuroscientists interested in understanding learning and plasticity in the brain began looking at the techniques used to train ANNs and found that some of the same principles could theoretically be in operation in the brain.

This has led to a huge increase in research using AI systems to model various aspects of animal behavior and cognition. There is also a renewed hope that neuroscience will provide additional insights for the development of new ANN approaches that can further advance the state of AI moving forward.

III. AI in agricultural biotechnology:

Biotechnology firms are utilizing AI/ML solutions to develop autonomous robots capable of handling crucial agricultural tasks, such as harvesting crops faster than humans [5]. Computer Vision and DL algorithms are used to process and analyze data captured by drones, enabling monitoring of crop and soil health. ML algorithms help in tracking and predicting environmental changes, including weather changes that impact crop yield. Digital transformation is also impacting smart agriculture, with many isolated solutions in digital ecosystems. An "Agricultural Data Space" like the Fraunhofer lighthouse project "Cognitive Agriculture" (COGNAC) can offer valuable added value.

An example of this is the evaluation of ecological and economic sustainability via the nutrient cycle. A balanced and appropriate nutrient cycle is essential for efficient, productive, and sustainable production of crop and livestock products. In dairy farming, data on feeding and milk yield can be collected to optimize nutrient cycling. However, optimizing nutrient cycling requires complete and sufficient quality data. Interoperability, uniform ontologies, and cognitive processing of data are crucial components.

AI in agriculture can provide food security by adapting agricultural management to changing climates, including identifying resistant crops. Molecular biology tools, such as molecular breeding, genetic manipulation of DNA to improve animal or plant traits, and plant tissue culture techniques have been applied for rapid plant production, disease resistance, conservation of endangered species, and genetic transformation. These technologies aim to improve crop performance in agriculture, resulting in genetic preservation, uniform plant growth, increased efficiency, and year-round production regardless of season.

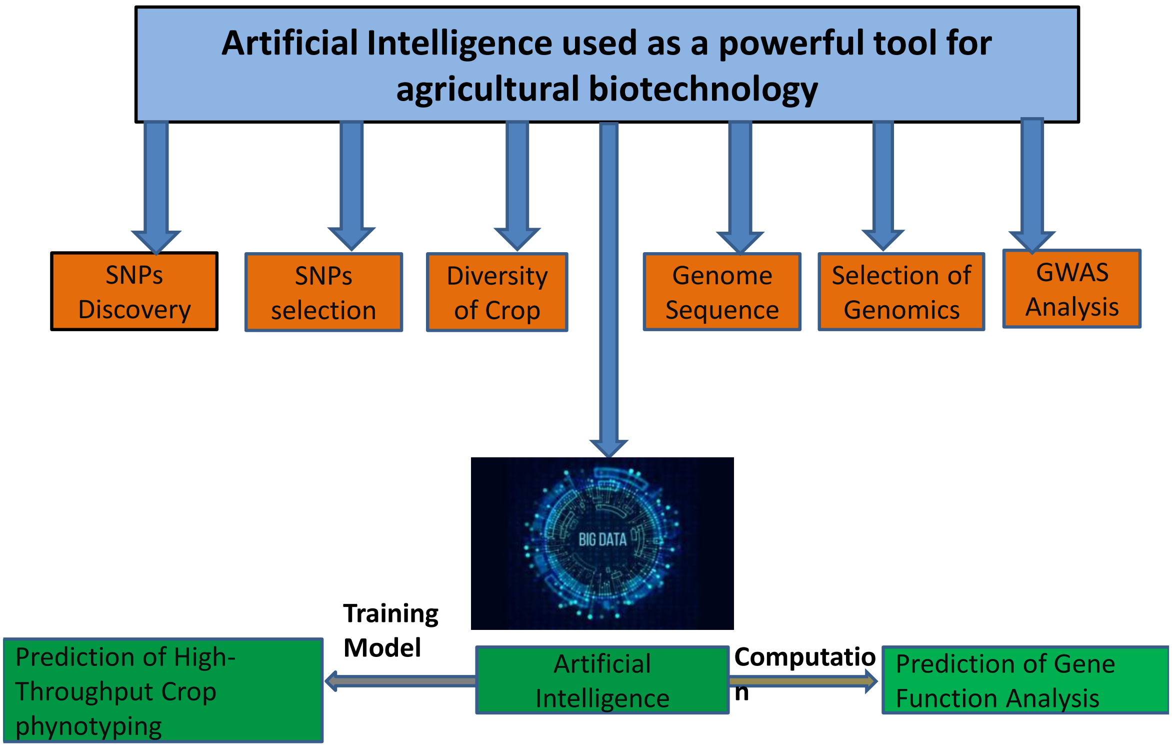


Figure 2: Artificial Intelligence used as a powerful tool for the prediction of high-throughput crop phenotyping and gene functional analysis in modern crop breeding. The high-throughput phenotypic and genotypic data were collected from large crop germplasm and breeding populations. The massive comprehensive database could integrate various resources with AI technology, such as phenotypic diversity of crops, SNPs polymorphisms, QTL analysis, GWAS analysis, genomics selection, and genome sequence. AI technologies are applied to predict the crop phenotype with whole genome prediction, the novel breeding strategies are produced through AI related to computation and training models.

• **Predictive modeling** AI can use data from satellite and drone imagery to predict tree growth and yield, optimizing forest planting and management. Advanced imaging techniques enable non-invasive visualization of tumor extent and metabolic activity, playing a crucial role in oncology patient diagnostic work-ups and surveillance. However, current tumor staging and surveillance criteria are primarily based on anatomic criteria. Clinical evaluations are often basic, relying on size measurements and response to treatment, with qualitative assessments of tumor characteristics like homogeneity and shape. This is possible due to the ease of making size measurements and the universality of image display and analysis platforms. However, there is a risk of under-utilization of substantial information, potentially wasting valuable information for tumor evaluation and treatment planning for oncology patients.

The skeleton is crucial for human motion and activities, but bone density decreases with age. Common bone diseases like osteoporosis and Paget's are common in the elderly, and a combination of multiple drugs is the optimal treatment. Artificial intelligence (AI) can evaluate drug-drug interactions (DDIs) and their underlying adverse effects. This research developed an AI-based machine-learning model to predict outcomes of interactions between drugs used for osteoporosis and Paget's treatment, reducing the cost and time of implementing the best combination of medications in clinical practice. A DDI dataset was collected from the DrugBank database, and chemical features were extracted from the simplified molecular-input line-entry system (SMILES) of defined drug pairs. Machine-learning algorithms were used to learn these features. The stack ensemble model from Random Forest and XGBoost achieved an average accuracy of 74% in predicting DDIs, showing the potential of AI models in predicting DDIs for osteoporosis-Paget's disease and other diseases.

IV. Disease and pest management:

AI can be utilized to analyze data on diseases and pests in forests, predicting their impact on tree health and productivity[6]. This can help identify areas at risk and implement preventative measures to protect forests. Modern agriculture faces significant challenges due to the competitive and globalized industry, requiring farmers to consider climatic, geographical, economic, and political factors. To meet the growing world population's nutrition demand, food production needs to increase, but arable areas are limited. The use of agricultural products for bioenergy adds pressure to food requirements, while housing and transportation issues further restrict arable land. Climate change has led to increased precipitations, global warming, droughts, and extreme weather events, endangering traditional production areas and introducing new risks and uncertainties for agriculture. Climate change also increases pest outbreaks, leading to increased international exchanges of infested material. Pest-related issues such as pesticide resistance, secondary pest outbreaks, and host plant resistance have also increased the agricultural production problem. To address these challenges, a continuous and sustainable

increase in productivity in all agricultural production areas is needed, while water, energy, pesticides, and fertilizers should be used diligently and efficiently.
Agriculture faces challenges and uncertainties, necessitating new solutions for all aspects of production. Integrated Pest Management (IPM) is the most popular and sustainable approach to controlling pests, but requires extensive knowledge, expertise, and observation. IPM involves monitoring pests in the field, determining their sensitive stages, and choosing the most appropriate control tactic. This requires intensive field observation, trained staff, and data mining. Artificial intelligence (AI) algorithms are now essential for controlling, tracking, and using agricultural inputs optimally. This chapter examines the impact of Industry 4.0 on modern agriculture and the innovations in IPM in information technologies. The development of Industry 4.0 has significantly impacted modern agriculture, necessitating new solutions for improved agricultural production.
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Deep learning technology has been used in various fields, including image-based pest and disease recognition research. However, building deep learning models requires large amounts of high-quality training data. Challenges include collecting large amounts of data on crop pests and diseases, which are seasonal and difficult to collect for rare, destructive pests like fire blight.

Building high-quality data is crucial for AI training, but labeling is essential for accurate diagnoses. However, there is a shortage of experts to handle cases where different pests and diseases have similar damage symptoms, leading to inaccurate diagnoses.

To ensure consistent data quality, a comprehensive data management system is needed. Multiple data sources, such as image, location, plant, disease, and pesticide info, are essential for efficient pest and disease monitoring and image-recognition-based diagnosis. This data must be managed in a standardized format using an integrated data management system that can expand for long-term use.

V. Environmental monitoring:

This paper presents a novel integrated information system (IIS) that combines Internet of Things (IoT), Cloud Computing, Geoinformatics, and e-Science for environmental monitoring and management[7]. The IIS uses multi-sensors and web services to collect data, while public and private networks access and transport mass data. Key technologies and tools include real-time operational database (RODB), extraction–transformation–loading (ETL), on-line analytical processing (OLAP) and relational OLAP (ROLAP), naming, addressing, and profile server (NAPS), application gateway (AG), application software for different platforms and tasks (APPs), IoT application infrastructure (IoT-AI), GIS and e-Science platforms, and representational state transfer/Java database connectivity (RESTful/JDBC).

Application Program Interfaces (APIs) are implemented in the middleware layer of the IIS, providing functions for storing, organizing, processing, and sharing data and information, as well as functions in environmental monitoring and management.

The case study on regional climate change and its ecological effects in Xinjiang reveals an increasing trend in air temperature and precipitation over the last 50 years. Water resource availability is a decisive factor for the terrestrial ecosystem in the area. The IIS greatly benefits research work, improving data collection, web services, and applications based on cloud computing and e-Science platforms. This paper provides a prototype IIS for environmental monitoring and management, providing a new paradigm for future research and practice, especially in the era of big data and IoT.

VI. AI in medical biotechnology:

The European In Vitro Diagnostics Regulation (IVDR) includes AI algorithms in its requirements, which presents significant challenges for companies using AI for data analysis and decision support[8]. However, if ethical and legal issues are addressed, stakeholders can benefit from data collection and evaluation. The full data tracking process, including sustainable crop production, real-time positioning, animal health monitoring, transportation, food processing, and storage, can improve consumer health and safety. This data on environmental and health conditions can ensure animal welfare and wellbeing. Tracing animal products can create big data, facilitating closed cycles, reducing inputs, saving resources, and reducing greenhouse gas emissions. Carbon taxes could increase beef prices by over 100% without considering the actual effects of the energy crisis, which accelerates costs for fossil fuel and fertilizer.

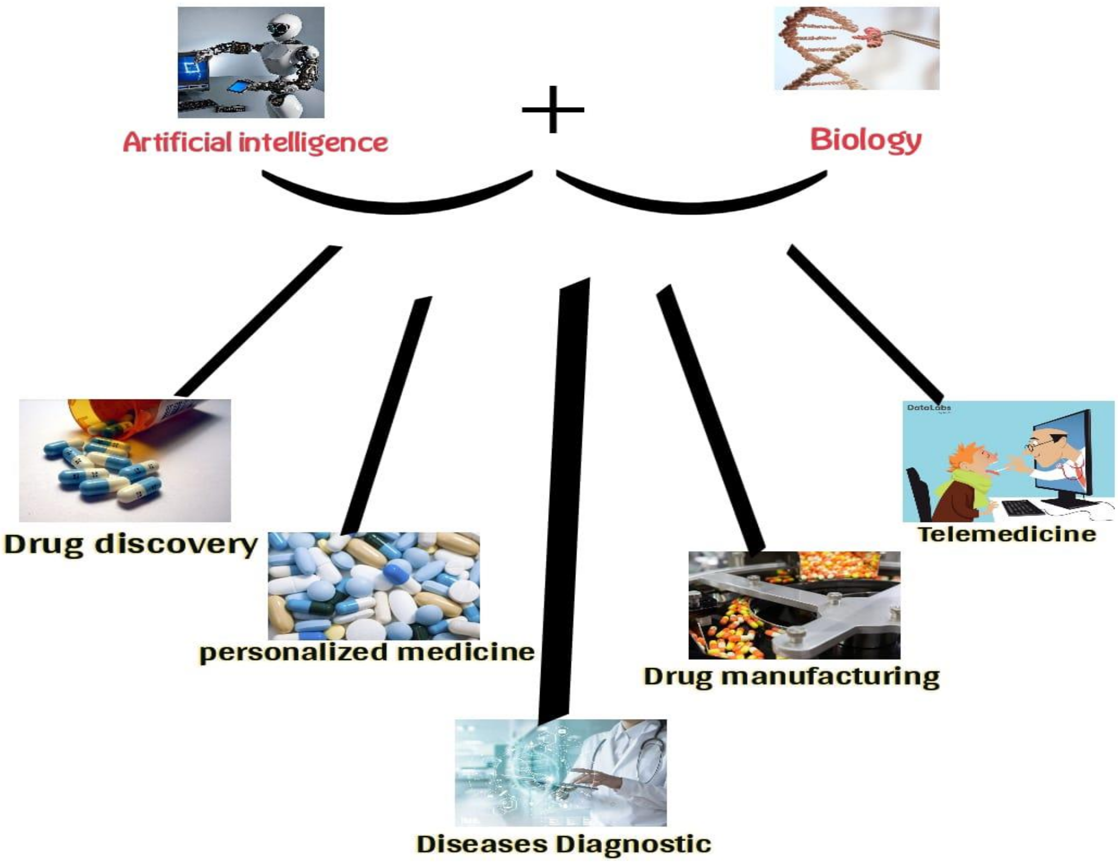

Figure 3: Future of Biotechnology in Artificial Intelligence in Medics

2. Rise of AI in Biological Sciences:

Artificial intelligence (AI) has the potential to significantly improve human life quality. As AI matures with more trained algorithms, its applications in epidemiology, host-pathogen interactions, and drug design expand[9]. AI is now used in drug discovery, customized medicine, gene editing, radiography, image processing, and medication management. AI-based technologies will enable more precise diagnosis and cost-effective treatment in the near future. In agriculture, AI-based approaches have reduced waste, increased output, and time to market. Machine learning and deep-learning-based smart programs can modify metabolic pathways of living systems to achieve optimal outputs with minimal inputs. This article summarizes the potential of AI in various fields of biology, including medicine, agriculture, and bio-based industry. The article highlights the potential of AI in improving human quality of life and enhancing the efficiency of bio-based industrial setups[10].

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3. Significance and Scope of AI in Biology:

Artificial intelligence (AI) refers to computerized systems that work and react in ways that require intelligence. AI technologies and methodologies are used in various biological sciences and biology R&D, including engineering biology[11]. AI has enabled advances in research and development across various industries, such as analyzing genomic data to determine the genetic basis of traits and potentially uncover genetic markers linked to those traits.

Artificial Intelligence in Image Analysis

Biology is complex and time-consuming, with image analysis being a challenging task due to the heterogeneity of samples, human error, complex tasks, and large amounts of data[12]. AI is helping to simplify and speed up these issues, such as Aivia from Leica Microsystems, which uses machine learning to classify objects and pixels in images and deep learning to restore and increase image resolution. AI can extract essential insights from large and complex images, making it easier to understand and improve patient outcomes. AI has also been successfully applied in infectious disease diagnosis, where skilled microbiologists or pathologists are not immune to human error. A recent review concluded that AI has the potential to speed up these diagnoses, increasing timely and accurate outcomes.

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I. Using Artificial Intelligence to Predict Protein Structure

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Understanding the structure of all proteins has the capacity to revolutionize all areas of biology, ranging from understanding diseases to comprehending the enzymes involved in the evolution of life as we know it.

As AlphaFold is a relative newcomer to the field, its full implications are not yet fully understood, but they are likely to be far-reaching and long-lasting.
Furthermore, the software is available for researchers to use. So, if you are working on a protein in the lab whose structure is unknown, why not discover its predicted structure using AlphaFold.

II. Artificial Intelligence in Drug Discovery

Drug discovery traditionally involves complex and time-consuming screens to identify potential compounds within a library. However, AI and machine learning can help overcome these challenges. AI can accurately predict the properties of potential compounds, avoiding wasted time and money. It can also help develop new compounds by creating molecules with predicted success properties, improving drug discovery and development. AI can also eliminate repetitive tasks in assessing drug effectiveness. For example, AI has helped develop a novel anti-cancer drug, an A2 receptor antagonist, which helps T cells attack cancers. Overall, AI and machine learning can significantly improve drug discovery and development.

(B). Fundamental of Artificial Intelligence:

I. Machine Learning Basics:

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II. Deep Learning and Neural Networks:

Which modifiable components of a learning system are responsible for its success or failure? What changes to them improve performance? This has been called the *fundamental credit assignment problem* (Minsky, 1963)[16]. There are general credit assignment methods for *universal problem solvers* that are time-optimal in various theoretical senses . The present survey, however, will focus on the narrower, but now commercially important, subfield of *Deep Learning* (DL) in *Artificial Neural.*

III. Natural Language Processing:

Natural language processing (NLP) is a computer system that analyzes and understands human languages like English, Japanese, Italian, or Russian. It can interpret text, build databases, generate summaries, or maintain user dialogues. This article focuses on issues in natural language comprehension and generation from text or keyboard input, aiming to improve database and information retrieval capabilities.

IV. Computer Vision in Biological Context:

This book explores the neuroscientific study of neuronal computations in the visual cortex, the psychological understanding of visual cognition, and the burgeoning field of biologically inspired artificial intelligence[17]. It covers topics such as neurophysiological investigation of the visual cortex, visual illusions, visual disorders, deep convolutional neural networks, machine learning, and generative adversarial networks. The success of computer vision relies on a deep understanding of the neural circuits in the brain responsible for visual processing. This resource is ideal for students and researchers looking to bridge different approaches to studying and developing visual systems.

(C). Application of AI in Biological Research:

I. Genomics and Bioinformatics

Coronaviruses have the largest genomes among all known RNA viruses, allowing them to accommodate and modify genes more effectively. The G+C contents of coronavirus genomes range from 32% to 43%. Both the 5' and 3' ends of coronavirus genomes contain short untranslated regions. The genome organizations of all coronaviruses are similar, with the characteristic gene order 5'-replicase ORF1ab, spike (S), envelope (E), membrane (M), and nucleocapsid (N)-3'. A transcription regulatory sequence (TRS) motif is present at the 3' end of the leader sequence, which is believed to mediate the unique random template switching during RNA replication, leading to a high frequency of homologous RNA recombination in coronaviruses.

II. Medical Imaging and Diagnostics:

Medical imaging is a medical technique that involves examining the interior of a body for clinical analysis and intervention, as well as visual representation of organ or tissue function[18]. It aims to reveal internal structures hidden by skin and bones, diagnose and treat diseases, and establish a database of normal anatomy and physiology to identify abnormalities. Although imaging of removed organs and tissues can be performed for medical reasons, they are typically considered part of pathology. Other imaging techniques, such as electroencephalography (EEG), magnetoencephalography (MEG), and electrocardiography (ECG), are not primarily designed to produce images but can be considered forms of medical imaging in another medical instrumentation discipline. As of 2010, 5 billion medical imaging studies were conducted worldwide, with radiation exposure from medical imaging accounting for about 50% of total ionizing radiation exposure in the United States. Medical imaging equipment is manufactured using semiconductor industry technology, with annual shipments of medical imaging chips amounting to 46 million units and $1.1 billion.

III. Precision Medicine with AI:

The convergence of artificial intelligence (AI) and precision medicine promises to revolutionize health care. Precision medicine methods identify phenotypes of patients with less-common responses to treatment or unique healthcare needs[19]. AI leverages sophisticated computation and inference to generate insights, enables the system to reason and learn, and empowers clinician decision making through augmented intelligence. Recent literature suggests that translational research exploring this convergence will help solve the most difficult challenges facing precision medicine, especially those in which nongenomic and genomic determinants, combined with information from patient symptoms, clinical history, and lifestyles, will facilitate personalized diagnosis and prognostication.

IV. Protein Structure Prediction:

Protein structure prediction and engineering-design aim to bridge the gap between sequence and structure space. Methods for protein structure prediction include ab initio methods, threading, and homology modeling [20]. Ab initio methods use evolutionary information from genomic sequences to compute protein 3D structures from amino acid sequences, while de-novo methods rely on first principle laws of physics and chemistry. Threading or fold recognition searches the protein structure template in a library with the lowest energy for the query sequence. Homology modelling uses the protein sequence identity between the input protein sequence and template structure to construct the 3D structure.

Procedures and challenges to protein structure prediction are discussed in numerous review articles. After modeling, the structure is checked using tools like PROCHECK, MOLPROBITY, VERIFY_3D, and WHAT_CHECK. 3D structures of proteins allow for structural analyses like functional annotation, interaction pathway analyses, and target drug identification. Protein-protein interactions are mediated by hydrophobic interactions and H-bonds, which are crucial for designing and engineering functional assemblies. Numerous algorithms have been developed to understand these interactions.

The DeepMind AlphaFold2 (AF2) deep learning method demonstrated exceptional performance in blind protein structure predictions during the 2020 Critical Assessment of Protein Structure Prediction (CASP14) [21]. The RosettaFold method also demonstrated excellent modeling accuracy on natural proteins and was particularly successful in modeling de novo designed proteins. Modified approaches with AI platforms can often reliably model protein-protein complexes and multimeric assemblies.

The Protein Structure Validation Software suite (PSVS) integrates multiple tools for protein structure validation, with a particular focus on protein NMR structure validation. PSVS provides knowledge-based protein structure validation tools, such as Molprobity clash and Ramachandran backbone analyses, Verify3D and ProsaII protein fold analysis tools, and PDBStat software for distance and dihedral angle restraint violation analysis.

6. Biomedical Data Analysis:

The research focuses on imaging analytics, machine learning, pattern recognition, and computational imaging, with a primary clinical focus on clinical neuroscience, cancer, and chronic kidney disease. The primary clinical research studies include brain development, brain diseases like Alzheimer's, schizophrenia, depression, and addiction, pediatric kidney diseases, and predictive modeling of cancer treatment outcomes[22]. Artificially intelligent computer systems are used extensively in medical sciences, with common applications including diagnosing patients, drug discovery, improving communication, transcribing medical documents, and remotely treating patients. Recent algorithms have achieved accuracies at par with human experts, and some speculate that artificial intelligence may soon replace humans in certain roles. This article aims to discuss the ways artificial intelligence is changing the medical science landscape and separate hype from reality.

V. Biological Network modeling:

AI-based techniques, such as artificial neural networks and genetic algorithms, can accurately capture the dynamics of biological systems and make predictions about their behavior under different conditions[23]. They can also aid in drug discovery and development by applying machine learning algorithms to large datasets of molecular structures and their associated biological activities. AI can model protein-ligand interactions, predicting the binding affinity of a ligand to a protein and the location and orientation of the ligand within the protein's active site. AI has shown promising applications in understanding and analyzing complex hierarchical biological networks, allowing researchers to identify critical biological components and their interactions. AI can also assist in the discovery of new drugs or therapies by predicting the effect of a drug on a particular biological component or pathway [24]. The increasing importance of AI in Systems Biology, which involves the holistic study of biological systems holistically and integratively, focuses on analyzing large and complex datasets, developing molecular-level models, and assisting in drug discovery and development.

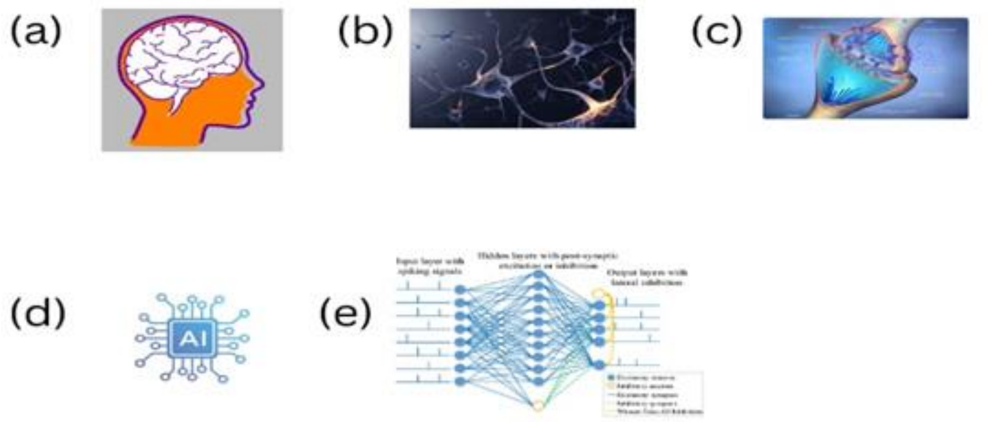


Figure 4: Schematic diagram of biological and artificial computing systems. a) The human brain. b) The biological neural network. c) A biological synapse. d) A biological neuron. e) An AI chip.

(D). AI for Healthcare and Disease Management:

I. Disease Diagnosis and Prognosis:

Artificial intelligence (AI) and machine learning (ML) are powerful tools used to analyze and predict data, rules, and instructions [25]. These technologies are particularly useful in cancer prediction, a chronic, aggressive, and unpredictable disease with low survival rates. However, challenges such as limited involvement in medicine, accessibility for racial minorities, and difficulty distinguishing between benign growth and other disorders persist.

Image-based risk models are being developed by researchers, but they require extensive scientific proof and computational advancement. Factor models assign a person the probability of a future unfavorable outcome over a specific time period. AI, ML, and DL are useful in early cancer prediction, improving the chances of cure and survival.

Aberrant DNA methylation could be a significant biomarker for tumor diagnosis, therapy, and prognosis, as it is closely connected to various disorders and is typically more stable than gene regulation. These tools can help improve early cancer diagnosis, therapy, and prognosis.

II. Personalized Treatment Approaches:

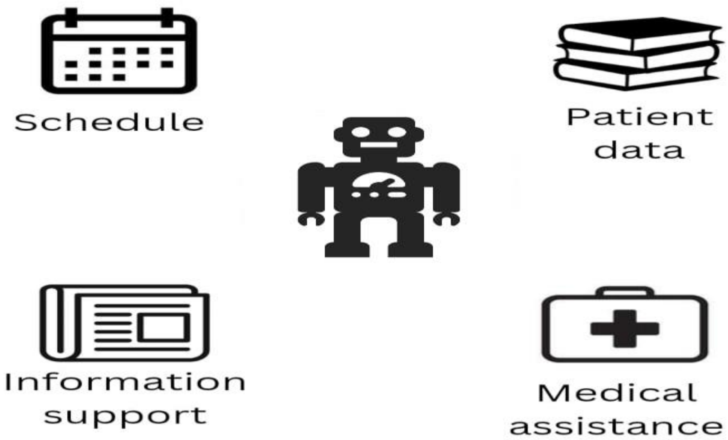
High-throughput biomedical research assays have led to the development of strategies for analyzing and interpreting vast amounts of data, with artificial intelligence (AI) being particularly suitable for this purpose. AI can play a crucial role in the development of personalized medicines, as data-intensive assays reveal appropriate intervention targets and treatment strategies [26]. However, AI's ability to advance personalized medicine depends on refining relevant assays and storing, aggregating, accessing, and integrating the data produced. Limitations of AI techniques in developing personalized medicines are also highlighted, along with areas for further research.

III. Healthcare Chatbots and Virtual Assistants:

AI-powered chatbots are revolutionizing the healthcare industry by providing virtual assistants that can manage conversations through speech or textual methods [27]. These bots adapt to individual language usages, searches, and preferences, making primary healthcare affordable, accessible, and potentially sustainable in the digital economy. They offer significant opportunities for tele-health delivery, particularly for patients with chronic diseases, disabilities, and those living in rural areas. AI-enabled virtual assistants provide 24x7 care, reducing time for physicians, improving data security, on-demand healthcare information, and an intuitive interface[28]. The advent of AI has allowed virtual assistants to penetrate various sectors, making healthcare more accessible and affordable for all.

The healthcare industry is undergoing a transformation with the integration of AI technologies, particularly chatbots and virtual assistants. Design characteristics play a crucial role in optimizing user experience. HidocDr, a key player in AI-driven healthcare, exemplifies the transformative potential of AI solutions through its Dr'sChatbot. AI chatbots play a pivotal role in patient engagement, administrative efficiency, personalized health information, remote monitoring, and addressing language barriers [29].

Figure5 : AI powered Chatbots in Virtual Assistance .



(E) AI in Ecolology, Environment, and Conservation:

I. Ecosystem Monitoring and Biodiversity:

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II. Predictive Models for Climate Change:

Machine Learning:

Plant pathology has long utilized statistical methods, including regression analysis and machine learning. Machine learning encompasses statistical methods in general and provides new approaches to prediction and classification using massive data sets like images and videos. Older methods often emphasize inference and estimation, while newer methods often emphasize prediction. Common statistical applications in plant pathology include analyzing designed experiments to understand the relationships between predictors and responses.

Machine learning communities are developing improved algorithms for various applications, such as surveillance strategies for Xylellafastidiosa. Algorithms often include wrappers to find optimal values of hyperparameters and build new models based on the shortcomings of earlier models. Cross-validation is used to evaluate predictions for data not used in learning the model.

However, optimization options in machine learning can result in overfitting, which is constructing a predictive model that is overly specific to the data used for learning [31]. A common weakness in machine learning is the inability to perform with new types of data, particularly in the context of climate change. Global analyses generally include interpolation and extrapolation, but do these methods provide predictions useful for finer-scale economic decision-making?

Advances in deep learning methods have made new options available for extremely detailed data sets, such as images and videos, weather prediction, and disease management [32]. Neural networks have also been used in plant pathology for decades, but greater computational speed broadens the opportunities for using deep learning.

Combining deep learning methods with other approaches has the potential to provide the best of both worlds. Digital agriculture has the potential to incorporate robotics into disease management through ground robots, offering value through automated detection and targeted treatment.

III. Wildlife Conservation and Monitoring:

Wildlife conservation is a critical issue involving the protection of endangered species and their habitats. However, challenges such as poaching, illegal trade, habitat loss, and climate change pose significant threats. Artificial intelligence (AI) can help overcome these challenges by processing and analyzing large amounts of data quickly and accurately. AI can detect patterns that humans may not be able to detect, identify endangered species, monitor their movements, and predict their behavior. Examples of AI in wildlife conservation include the TrailGuard AI system developed by Resolve, which uses motion sensors and cameras to detect poachers in protected areas and alert rangers in real-time[33]. The National Oceanic and Atmospheric Association (Noaa) has partnered with Google AI for Social Good to create an ML model that can recognize whale songs and monitor them in the ocean. However, there are challenges and limitations to address, such as the cost of implementing AI systems and the potential for AI to replace human involvement in conservation efforts. In the future, AI could be used to predict climate change impacts on endangered species, identify vulnerable areas, and develop more effective conservation strategies.

IV. Environmental Impact Assessments:

Wildlife conservation is a critical issue involving the protection of endangered species and their habitats. However, challenges such as monitoring animal movements, poaching, illegal trade, habitat loss, and climate change pose significant threats to wildlife populations[34]. Artificial intelligence (AI) can help overcome these challenges by processing and analyzing large amounts of data quickly and accurately. AI can detect patterns that humans may not be able to detect, identify endangered species, monitor their movements, and predict their behavior [35].

(F). Ethical, Legal, and Social Implications(ELSI):

I. Data Privacy and Security:

Technological advancements and increased computer power have led to the implementation of artificial intelligence (AI) in various applications. As society grows with increasingly advanced and interconnected conditions, the importance of security solutions and prevention measures will increase. Machine learning models are used to promote innovation in healthcare, gaming, and the economy, while deep learning models are used by autonomous vehicle manufacturers to develop pipelines for self-driving vehicles [36]. These algorithms automate jobs and processes, giving them unprecedented abilities and functions. However, many AI models are susceptible to attacks that circumvent privacy, security, integrity, or accessibility by using inputs designed to cause inaccurate predictions. AI systems are often developed with little attention to security, making them vulnerable to hostile examples [37]. During the machine learning training and testing phases, adversarial attacks on AI systems can occur, such as "poisoning attacks," which are simple to execute in systems that use training data from unreliable sources.

AI Based Drones for Security Concerns in Smart Cities:

Artificial intelligence (AI) is a rapidly emerging technology that mimics human brain functioning to solve real-life problems. It has applications in various fields such as robots, smart cars, e-commerce, navigation, human resource, healthcare, agriculture, gaming, automobile, social media, and marketing. AI security refers to tools and techniques that use AI to autonomously identify and respond to potential cyber threats based on similar or previous activity. AI algorithms are used to detect malware, run pattern recognition, and detect even the smallest behavior of malware before it enters the system. With fast-evolving cyber attacks and rapid device multiplication, AI and machine learning can help keep abreast with cybercriminals, automate threat detection, and respond more effectively than conventional software-driven or manual techniques. AI can also help detect cyber threats and malicious activities in the cyberworld, and in combination with natural language processing, it can extract patterns from textual data to find potential threats. AI can also battle with bots, which can create bogus accounts with stolen credentials.

This paper discusses the concept of smart cities and how AI-based systems are being used for their management. It also discusses how blockchain technology can empower smart cities, and how AI-based drones can enhance surveillance of events. The paper also discusses the security concerns in cities and how they are addressed with AI-based drones. In conclusion, emerging technology such as blockchain can help improve the management of smart cities.

Data Protection in AI:

Data protection is crucial for AI models, as it contains sensitive information and can lead to privacy violations if misused. The quality and representativeness of training data are essential for accurate, fair, and reliable AI models[38]. To safeguard sensitive data, policies and practices must be implemented, including access controls, security measures, data anonymization, and encryption techniques.

Various approaches to maintain data integrity include data validation and cleaning techniques, anomaly detection and pattern analysis, and federated learning techniques. Data validation and cleaning ensure quality and eliminate biases, while anomaly detection and pattern analysis identify potential manipulations or malicious attacks. Federated learning techniques keep data in their original locations, minimizing exposure of sensitive data. Overall, data protection is essential for building trust in AI systems and ensuring the accuracy, fairness, and reliability of AI models [39].

II. Bias and Fairness in AI Algorithms:

Bias in data:

Bias in data can show up in several forms. Here are the top offenders:

Historical bias is the already existing bias in the world that has seeped into our data. This bias can occur even given perfect sampling environments and feature selection, and tends to show up for groups that have been historically disadvantaged or excluded. Historical bias is illustrated by the 2016 paper "Man is to Computer Programmer as Woman is to Homemaker," whose authors showed that word embeddings trained on Google News articles exhibit and in fact perpetuate gender-based stereotypes in society[40].

Representation bias is a bit different — this happens from the way we define and sample a population to create a dataset. For example, the data used to train Amazon's facial recognition was mostly based on white faces, leading to issues detecting darker-skinned faces. Another example of representation bias is datasets collected through smartphone apps, which can end up underrepresenting lower-income or older demographics.

Measurement bias occurs when choosing or collecting features or labels to use in predictive models. Data that's easily available is often a noisy proxy for the actual features or labels of interest. Furthermore, measurement processes and data quality often vary across groups. As AI is used for more and more applications, like predictive policing, this bias can have a severe negative impact on people's lives. In a 2016 report, ProPublica investigated predictive policing and found that the use of proxy measurements in predicting recidivism (the likelihood that someone will commit another crime) can lead to black defendants getting harsher sentences than white defendants for the same crime.

Fairness in AI Example:

Imagine we create a binary classification model, where we believe we have very accurate predictions:

Fairness can come into question if this data actually included two different underlying groups, a green and blue group. These groups could represent different ethnicities, genders, or even geographical or temporal differences like morning and evening users.

III. Regulatory Frameworks for AI in Biology:

Machine learning (ML) technologies are rapidly developing in various medical imaging applications, particularly in brain imaging. The goal is to translate safe and effective technologies to clinics for patient benefit[41]. Regulatory oversight plays a crucial role in this translation, with the Center for Devices and Radiological Health (CDRH) at the US Food and Drug Administration (US FDA) ensuring timely and continued access to safe, effective, and high-quality medical devices. This chapter discusses performance assessment of machine learning algorithms in imaging applications from a regulatory science perspective.

The primary topics discussed are concepts, basic principles, and methods for performance assessment of ML algorithms in regulatory science, but not regulatory policy[42]. The question of which components should be included in a specific regulatory submission depends on factors such as device risk, impact on clinical practice, technology complexity, and precedents.

The topics selected are based on experience and expertise but are not intended to be comprehensive. ML algorithms are developed for both imaging and non-imaging modalities for treating brain disorders, with most discussions applicable to ML algorithms in general imaging applications [43]. Assessment methods are well established, but better methods may become available and adopted by researchers, developers, and regulatory agencies in the future.

To provide readers with a more specific sense of the scope of applications relevant to these discussions, the American College of Radiology (ACR) and FDA public databases were reviewed to summarize major scope characteristics including imaging modalities, functionalities, and types of ML algorithms.

IV. Societal Acceptance and Adoption Challenges:

Artificial Intelligence (AI) technologies are increasingly being used in various aspects of human life, including migration[44]. This field is particularly complex due to its political sensitivity and divisive nature, as well as the high vulnerability profiles of migrants who have little chance of protection from the intended or unintended effects of technology.

Social acceptance of AI technologies is crucial, as they can be used for border control, generating new knowledge on migration and migrants, detecting emerging trends in migration, understanding migrants' experiences, recognizing their material and social needs, and detecting human rights violations. While some argue that AI technologies are always harmful when applied to migrants, it is essential to consider whether it is possible to block the use of these technologies while reducing risks while expanding their potential benefits.

Identifying the actors who are asked to accept AI technologies applied to migration is also problematic [45]. With the growing fragmentation and diversification of social life in late modernity, identifying well-defined social groups and dominant "public opinion" has become increasingly difficult. Personal orientations, attitudes, choices, or lifestyles have an increasing weight in defining how individuals deal with public issues such as technologies or migration, while other social variables like professional group affiliation, income class, living conditions, or religious beliefs have less influence on people's thinking and behaviors.

In conclusion, the use of AI technologies in migration is a complex and politically sensitive area, and it is essential to consider how risks can be reduced while enlarging their potential benefits [46].

Artificial Intelligence (AI) technologies, including machine learning, rule-based systems, natural language processing, and speech recognition, are gaining momentum as disruptive technologies in various industries [47]. They are also beginning to be adopted in the public sector, such as education, social policy, and regulation. AI systems can predict which school teacher will have the greatest value added, while social policy uses AI to predict high-risk youth for targeted interventions [48].

However, the hype surrounding AI adoption in the public sector is accompanied by uncertainty. While AI applications are seen as enablers of increased efficiency and effectiveness, they also pose challenges such as job destruction, privacy infringements, and reinforcement of biases in policy-making [49]. The healthcare sector is a key area of adoption of AI technologies, with high investments in new technologies. AI has the potential for transformative work, such as mining medical records, assisting repetitive jobs, and designing treatment plans [50]. However, the healthcare sector presents unique characteristics due to its ecosystem of stakeholders, including government agencies, service-delivering public organizations, and private IT firms providing technology.

Despite the media hype, there is still little research on AI in the public sector. There is little empirical research to test assumptions or provide guidelines for the governance of this emerging phenomenon. This study aims to fill this gap by addressing the perceived challenges of AI adoption in the public healthcare sector.

In conclusion, AI technologies are becoming increasingly prevalent in various industries, including education, social policy, and regulation. However, there is still much uncertainty surrounding the challenges and opportunities presented by AI adoption in the public sector [51].

This study explores the challenges of adopting IBM Watson, an AI system, in China's public healthcare ecosystem. The research focuses on government policy-makers, hospital managers/doctors, and IT firm managers. China's healthcare services are heavily influenced by public sector intervention in regulation, strategy, and financing. Watson, developed by IBM, is being introduced in some regions to answer natural language questions and design personalized treatment plans based on medical literature [52]. The study aims to map the challenges of AI adoption by key stakeholders in the public sector, allowing for a better understanding of AI impacts beyond speculation..

(G). Future Directions and Emerging Trends:

I. Advancements in AI Technologies:

Artificial Intelligence (AI) has become a transformative and influential technology in the 21st century, revolutionizing the way we perceive technology, interact with machines, and make decisions [53]. Its diverse applications have sparked both enthusiasm and debate about its implications for society, ethics, and the future. The genesis of AI can be traced back to the inception of computer science, where early pioneers envisioned machines that could simulate human intelligence [54]. Over the decades, this vision has evolved from theoretical concepts to tangible implementations, driven by exponential advancements in computational power, data availability, and algorithmic innovation [55].

AI's hallmark lies in its ability to learn from data, recognize patterns, and make predictions or decisions with remarkable accuracy [56]. This prowess has propelled AI into numerous domains, transcending traditional boundaries and reshaping industries. For example, AI-driven diagnostics and personalized treatment recommendations promise more effective patient care in healthcare, predictive analytics and algorithmic trading systems revolutionize investment strategies in finance, and autonomous vehicles in transportation redefine mobility [57].

However, ethical considerations and societal implications remain large, with questions regarding data privacy, algorithmic bias, job displacement due to automation, and the ethical use of AI. As AI systems become more autonomous and embedded in critical decision-making processes, ensuring transparency, fairness, and accountability becomes imperative. Striking a balance between innovation and ethical responsibility remains a central challenge in the ongoing development and deployment of AI technologies [58].

IoT is a crucial component in the communication paradigm of everyday objects, enabling devices to communicate and become essential for smart cities [59]. It is used by national governments and private organizations in ICT solutions to manage the concept of smart cities, aiming to improve community resources, service quality, and operational and management costs. IoT technologies are essential in developing the landscape of current smart cities and guiding the standard to the enormous data scale [60]. According to Statista Research, by 2030, the global count of IoT-enabled devices is projected to exceed 29 billion, nearly three times the figure in 2020. IoT is considered one of the most valuable emerging technologies, bringing new opportunities and challenges in implementing intelligent applications and offerings. It is essential for the advancement and progression of diverse smart city applications, driving sustainable development and fostering innovative solutions.

IoT is a vital component in everyday objects, enabling communication and becoming cities for essential for smart [61]. It is used by governments and private organizations in ICT solutions to improve community resources, service quality, and operational costs. By 2030, the global count of IoT-enabled devices is projected to exceed 29 billion, nearly three times the 2020 figure. IoT is considered a valuable emerging technology, presenting new opportunities and challenges in implementing intelligent applications. It is crucial for the advancement of diverse smart city applications, driving sustainable development, and fostering innovative solutions [62].

This review article explores the concept of smart cities and the role of IoT in their development. It discusses the role of IoT in enabling devices to communicate and becoming essential components of smart cities [63]. The article also explores the potential of AI in analyzing the vast amount of data produced by IoT sensors in smart cities. It highlights how this technology can enhance city administration and lead to better living standards for residents.

The article is structured into several sections, including an introduction to smart cities, a definition of smart cities, IoT-based technologies necessary for creating smart cities, AI algorithms suitable for smart cities, future trends of smart cities, such as the integration of 5G communication technology, and the impact of AI on various applications.

The review article aims to provide a comprehensive overview of the current state and future directions of smart city development, highlighting the potential benefits of this emerging field for urban residents, governments, and businesses [64]. It also discusses the challenges and opportunities of integrating AI and IoT in smart cities, such as reducing human interaction and enhancing city administration. The article concludes by providing conclusions and prospects for the future of smart cities.

II. Integration of AI with other Technology:

Artificial intelligence:

AI is a field of information technology that focuses on managing technologies that learn to make decisions independently and carry out actions instead of human beings. It can replace entire systems, take decisions, or improve specific processes. AI is a generic term that includes software or hardware components that support machine learning, artificial neural networks, deep learning, cognitive computing, and natural language processing [65].

Recent progress has been made in the development of powerful AI techniques, with machine learning models increasingly useful for identifying hidden relationships within data [66]. The study of machine learning techniques is constantly evolving, with a growing focus on automated machine learning, reinforcement learning, and artificial neural networks.

Recurrent neural networks and convolutional neural networks are developing, mainly applied to processing sounds, images, and videos. In production systems, ANN and machine learning techniques can analyze historical data of production processes and identify optimal parameter combinations to improve efficiency, reduce production time, or minimize material waste [67].

In conclusion, AI is a rapidly evolving field that aims to improve efficiency, reduce production time, and minimize material waste. Advances in machine learning, artificial neural networks, and reinforcement learning are driving the development of more powerful AI techniques.
Deep learning is a machine learning method based on artificial neural networks, utilizing multiple layers to improve performance [68]. With increased computational power and data availability, it has made significant progress in predictive maintenance and demand forecasting. However, interpretability remains a challenge. New techniques have been developed to understand and visualize algorithms' workings, enabling more informed decisions.

Computer vision, a field of computer science, enables computers to observe, identify, and process images like human vision. Advances have been made in detecting specific objects within images, improving product tracking and inventory tracking. The field is also advancing in the generation of realistic, three-dimensional images [69].

Cognitive computing aims to solve complex problems with uncertainty and ambiguity, integrating different sources for informed, ethical, and responsible decisions. With the exponential increase of data, it is mainly used for complex resolution problems [70].

Natural language processing, which involves computer programs understanding spoken and written human language, has been developed to generate coherent and controlled text like ChatGPT [71]. It can be used to process supply contracts or order documents, reduce processing times, and analyze customer feedback for valuable information on preferences and performance improvements.

3D printing:
3D printing is a process that creates physical objects from CAD models or digital 3D models using layers of material fused together. This technology has improved manufacturing productivity by reducing lead times in prototyping and creating auxiliary devices for new product production. Rapid prototyping allows for greater innovation and experimentation while reducing costs. However, the speed of 3D prints is not high, making it less used in mass production [72].

There are various 3D printing techniques depending on the material layer and equipment used. For example, powder bed fusion uses a laser beam to create physical objects from powder layers, stereolithography creates three-dimensional objects from a liquid polymer, and polyjet builds parts by throwing droplets of photopolymer onto a build platform and solidifying them with UV light. These technologies are particularly useful in aerospace, automotive, and medical sectors, but are mainly used for small series or prototype production.

Bioprinting combines cells and biomaterials to create biomedical parts, simulating the natural features of tissues [73]. Fused filament fabrication and fused deposition modelling add layers of molten plastic to create models or products, mainly used for spare parts and replacement of damaged or obsolete components. Directed energy deposition uses focused energy sources to melt materials simultaneously deposited by a nozzle, reducing machine downtime and producing large parts that cannot be created with traditional methods. Binder jetting is a 3D printing process where an industrial print head selectively deposits a liquid binding agent on a thin layer of dust particles to build high-value parts.

Big data and data analytics:
Big data technology is a combination of unstructured, semi-structured, or structured data that can be collected and extracted to gain insights using predictive modelling and advanced analytics projects [74]. Its five main features are volume, velocity, variety, veracity, and value. Volume represents the initial size and amount of data collected, while velocity refers to the data generation rate. Variety refers to data diversity, with challenges in variety such as data standardization. Veracity refers to data quality and accuracy, while value refers to the activities companies can perform with the collected data.

The value of big data technology increases significantly when well implemented within production systems, allowing companies to better customize products and achieve high levels of satisfaction [75]. However, it presents challenges such as data protection, relevant data identification, and cleaning techniques for analyzing data with different formats. Data mining is a process that analyzes hidden patterns of data from different perspectives to obtain useful information [76]. Sentiment analysis and user behavior analytics are data mining techniques used to measure people's opinions and extract personal information from the web. These techniques help monitor customer satisfaction, make informed decisions on product and service improvements, support marketing strategies, and monitor competitors. User behavior analytics is a powerful methodology used to analyze and monitor the behavior of operators in the workplace, involving closely examining and interpreting data related to their actions, activities, and time spent working with machines.

Blockchain technology:
Blockchain technology is a distributed ledger that records data in blocks linked together using cryptography, ensuring linear and chronological storage. It is known for its role in cryptocurrencies and is increasingly used in production systems for its benefits such as product traceability, security, and efficiency [77]. Blockchain eliminates intermediaries and costs associated with transactions, allowing for faster completion and transparency.

In production systems, blockchain improves inventory management by providing real-time information to all actors in the network, facilitating collaboration and data sharing between stakeholders. However, there are challenges such as cost and inefficiency, the block size debate, and unclear government regulation regarding cryptocurrencies.

Another tool connected to blockchain is the smart contract, which is a code that can be integrated into the blockchain to facilitate and verify contractual agreements [78]. Smart contracts operate on predefined conditions agreed by users and are automatically executed when these conditions occur. These tools can facilitate various activities within supply chain management (SCM) and automate payments between parties involved only upon fulfilling predefined conditions, such as successful product delivery.

In conclusion, blockchain technology offers numerous benefits, including cost reduction, efficiency, transparency, and collaboration in various sectors. However, challenges such as block size debates and unclear government regulations remain.

Computing:
Cloud-related technology involves data storage on multiple servers and online access from any device [79]. It offers applications such as email, archiving, data backup, analytics, and on-demand software. Cloud-based software offers companies benefits such as cost savings in information management technologies and infrastructures, improved monitoring and maintenance of production equipment, and collaboration between teams through data sharing. However, there are risks associated with cloud computing, such as data security concerns and potential natural disasters, internal bugs, and power outages.

To improve inefficiencies, new tools and techniques have been developed, such as edge computing, fog computing, and cloudlet computing. Edge computing processes data as close to its origin to reduce network latency by minimizing communication times between client and server. Fog computing is an infrastructure interposed between edge and cloud computing to enable more efficient data processing, analysis, and storage. Cloudlets are small-scale data centers designed to quickly deliver cloud computing services to mobile and wearable devices, increasing response time of applications [80].

Real-time data analysis is performed directly in the proximities of items, reducing latency and enabling timely responses from data generated by sensors and production machines [81]. These systems are useful for early detection of anomalies or machine malfunctions. Quantum computing, based on quantum theory principles, can handle operations at significantly faster speeds and with lower power consumption, optimizing production processes to solve complex problems such as managing workflows or reducing production times.

Digital applications:
Digital applications, including social media & network, mobile applications, and web applications, have become essential tools for people and companies. Social media & network enable users to share content and interact with others, increasing sales through advertising, promotions, and customer service [82]. Mobile applications are software designed for smartphones and tablets, providing functions similar to PC applications. They are used in production systems for monitoring machines, updating order statuses, tracking material stocks and inventory, and facilitating real-time communication.

Web applications are software programs that run on a web server and require a web browser to access. They offer several benefits over desktop applications, such as not being developed for multiple platforms and not having direct access to updated versions. Web apps allow users to access data from multiple devices, planning production, allocating resources, managing inventory, and improving coordination of activities. They can also facilitate supplier relationship management through shared order management systems.

Robotic process automation is another digital application that automates routine business practices with software agents (bots) that perform tasks automatically. Bots digitally replicate human activities, automating activities without direct human intervention [83]. Technologies necessary for digitization in this area include digital signatures, electronic invoices, and digital contracts. Overall, digital applications have become indispensable tools for people and companies, enabling efficient use of resources, better coordination, and improved productivity.

Geospatial technologies:
Geospatial technologies are modern tools that aid in mapping and analyzing Earth's surface and human activities. Satellites have enabled the detection of Earth's surface images and human activities, while computers have enabled the storage and transfer of GIS data[84]. These technologies have been widely used in industrial engineering, agricultural, and environmental monitoring in the last decade. They map manufacturing resources, such as equipment, warehouses, and facilities, to identify efficient routes for resource management. The data collected can also identify areas of environmental importance for marketing and influence product demand. Geospatial technologies are also being used to improve safety at work by identifying high-risk areas and preventing employee health and safety [85].

Several geospatial technologies include remote sensing for data acquisition, web mapping, GPS for position, speed, and synchronization, and the global navigation satellite system for global Earth coverage. These technologies are used in logistics to track goods, monitor outbreaks, assess crop status, and target advertisements to specific users.

III. Potential Disruption and Transformations:

The Potential to Revolutionize Scientific Research:

multiple screenings and shortening analysis time, contributing to early diagnosis The capacity to analyze

enormous amounts of data and to perform labor-intensive tasks in short times, makes AI extremely appealing, stimulating researchers to explore applications in several scientific fields.
Molecular biology could benefit considerably from AI. There is a lot of interest in trying to predict the three-dimensional structure of proteins from DNA sequences. Similarly, many efforts are being made in astronomy and the study of the universe [86].
Space observations in fact produce huge amounts of data where instrumental artifacts need to be identified and removed before real data can be analyzed. AI and machine learning can perform this challenging task, “cleaning” data for later analyses.

Transforming Medical Imaging and Clinical Diagnosis:
There is an increasing interest in applying artificial intelligence techniques to medical imaging, particularly in the field of radionics, where a large number of quantitative features are extracted from medical images using data characterization algorithms.
AI can boost the healthcare sector by helping with the identification of tumors. Predictive models can be developed to identify regions of interest (ROI) or gross tumor volume (GTV) from images acquired via a scanner machine (e.g., MRI, CT-scan, PET).
Computers can be trained to distinguish between normal- and irregular-looking lymph nodes in computer tomography images, and a level of precision has been achieved in interpreting mammograms for breast cancer screening.
A cloud-based imaging platform (Arterys) that helps physicians track tumors on CT scans and MRI of lung and liver cancer patients, was approved by the food and drug administration (FDA) in 2018 [87]. While specialists can only analyze a limited number of images in their time, AI can contribute by performing.

IV. Research Opportunities and Challenges:

Artificial Intelligence (AI) is rapidly becoming a powerful tool for solving image recognition, document classification, and advancing interdisciplinary problems [88]. However, combining AI with other fields like neuroscience, developmental psychology, developmental robotics, and evolutionary biology can create communication barriers due to differences in terminologies, methods, cultures, and interests. To bridge these gaps, having a solid education in both machine learning and the field of interest is essential.

Advocating for ethics and diversity is crucial to account for biased models and avoid stereotypes perpetuated by AI systems [89]. Interdisciplinary approaches, including art and science, and ensuring minorities are well represented among users and evaluators of the latest eXplainable AI techniques can make AI more accessible and inclusive to otherwise unreachable communities.

The AI revolution is rapidly advancing in research, healthcare, and industry, but its long-term impact on society will not be immediately apparent. AI methods may be applied to problems that are not yet ready, leading to ethically questionable applications such as predicting sexual orientations from people's faces or using facial recognition in law enforcement or commercial use. AI can improve data privacy and threat identification, but it is often seen as a threat to IT systems.

In industry, AI chatbots have been racist due to training data presented to the algorithm, recruitment software has been gender-biased, and risk assessment tools developed by a US contractor have sent innocent people to jail. A more careful consideration of the impact of AI is needed by following global and local ethics guidelines for trustworthy and responsible AI.

(H). Case Studies and Emerging Trends:

I. Notable AI Application in Biology:

Artificial intelligence (AI) is the simulation of the human intelligence process by computers. The process includes acquiring information, developing rules for using the information, drawing approximate or definite conclusions and self-correction[90]. The advancement of AI can be seen as a double-edged sword: many fear that it will threaten their employment; by contrast, every advance in AI is celebrated because of the belief that it will vastly contribute to the betterment of society. AI is used in various sectors from innovating educational methods to automating business processes. The sprouting idea of adopting AI in the drug development process has shifted from hype to hope. In this review, the possible applications of AI in the drug development pipeline in drug development strategies and processes, the pharmaceutical R&D efficiency and attrition, and partnerships between AI and pharmaceutical companies are discussed. artificial intelligence (AI) are modernizing several aspects of our lives. The pharma industry is facing challenges to overcome the high attrition rates in drug development The pharma industry is collaborating with AI industries to overcome challenges AI will improve the efficiency of the drug development process..(AI) uses personified knowledge and learns from the solutions it produces to address not only specific but also complex problems. Remarkable improvements in computational power coupled with advancements in AI technology could be utilised to revolutionise the drug development process. At present, the pharmaceutical industry is facing challenges in sustaining their drug development programmes because of increased R&D costs and reduced efficiency. In this review, we discuss the major causes of attrition rates in new drug approvals, the possible ways that AI can improve the efficiency of the drug development process and collaboration of pharmaceutical industry giants with AI-powered drug discovery firms. modeling and target discovery are crucial initial steps in the drug discovery process and significantly impact on the success of drug development. Given the advantages of analyzing large datasets and complex biological networks, artificial intelligence (AI) is playing a growing role in modern drug target identification.

We discuss the use of deep learning models for target discovery, AI-identified targets validated through experiments, and the use of synthetic data produced using generative AI for target identification.

Novelty, in addition to drug ability and toxicity, is a crucial factor in target selection. There is a trade-off between choosing high-confidence and novel targets. Over the past few years several AI-derived drugs have entered clinical trials, signaling the dawn of a new era in AI-driven drug discovery.

Overview of target identification:

The drug discovery pipeline is widely recognized to be a time-consuming, expensive, and risk-laden process that typically requires around 10 years and $2 billion to bring a novel drug to market [91]. By 2022 fewer than 500 successful drug targets had been identified , representing a tiny fraction of the estimated druggable targets in humans . Although numerous drug candidates undergo extensive optimization during preclinical stages, the average failure rate in clinical trials from 2009 to 2018 reached 84.6%i . The lack of clinical efficacy remains the key factor contributing to the failure of both Phase 2 and 3 trials , leading to substantial financial losses and resource wastage. Identifying the right drug targets is crucial for increasing the likelihood of developing clinically effective therapies. Target identification, the process of identifying the right biological molecules or cellular pathways that can be modulated by drugs to achieve therapeutic benefits, is increasingly important in modern drug discovery. Although innovations in experimental and omic technologies have been growing over the past few decades, identifying actionable therapeutic targets remains challenging. The integration of multiomic data with AI (see Glossary) algorithms has recently emerged as a promising approach for target identification ii, iii. We discuss here the conventional target identification approaches with a focus on the application of AI algorithms to target identification. This paper aims to offer a progressive outlook on the emergence of the AI-driven drug discovery era and encourage the integration of AI technologies into drug discovery pipelines. Strategies in target identification: from experiments to machine learning Target identification can be classified into three distinct strategies – experimental, multiomic, and computational approaches. Using these methods collaboratively can generate novel therapeutic hypotheses in exploratory target identification, thus significantly enhancing our understanding of complex diseases.

The emergence of artificial intelligence (AI) in early drug development. (Upper panel) Key technological advances in the history of target identification are classified into three types: experiment-based (red), multiomic (blue), and computational (green) approaches. Traditionally, experiment-based methods have been the go-to approach for discovering therapeutic targets. However, with the rise of big data, integrated analysis of multiomic data has become a more efficient strategy for target identification. In addition, recent advances in AI-driven biological analysis have identified novel targets and AI-designed drugs are now entering clinical trials. (Lower panel) AI applications in the early stages of drug discovery. Abbreviations: AGC chemistry, affinity-guided catalyst chemistry; ALS, amyotrophic lateral sclerosis; DL, deep learning; EGFR, epidermal growth factor receptor; GAN, generative adversarial network; GWAS, genome-wide association study; LD chemistry, ligand-directed chemistry; MTOR, mammalian target of rapamycin; NSCLC, non-small cell lung cancer; SILAC, stable isotope labeling with amino acids in cell culture; TID, target identification. Figure created with BioRender.com [92].

AI-driven target identification:

In recent years we have witnessed an explosion of biomedical data ranging from basic research on disease mechanisms to clinical investigation in patients. Although large amounts of information have been generated, the growth of data also poses challenges for data analysis. This is where the emerging role of AI comes into play. Given the advantage of AI in processing and tackling complex biomedical networks of data, using AI algorithms can reveal patterns and relationships within the data that may not be apparent to humans, and may possibly lead to better understanding and treatment of diseases. AI has made notable contributions that facilitate biomarker and target identification , indication prioritization , drug-like molecule design , pharmacokinetics prediction , drug–target interaction, and clinical trial design [93]. Although still in the early stages of clinical trials, AI-derived drugs are increasingly emerging in clinical studies , as exemplified by GS-0976 for the treatment of non-alcoholic steato hepatitis, EXS-21546 for solid tumors, and INS018_055 for idiopathic pulmonary fibrosis, which is the first-ever AI-derived drug with positive topline results in a Phase 1 clinical trial.

II. Impact of AI in AI in Real-world Scenarios:

Artificial intelligence (AI) is a leading technology of the current age of the Fourth Industrial Revolution

(Industry 4.0 or 4IR), with the capability of incorporating human behavior and intelligence into machines or systems [94]. Thus, AI-based modeling is the key to build automated, intelligent, and smart systems according to today's needs. To solve real-world issues, various types of AI such as analytical, functional, interactive, textual, and visual AI can be applied to enhance the intelligence and capabilities of an application. However, developing an effective AI model is a challenging task due to the dynamic nature and variation in real-world problems and data. In this paper, we present a comprehensive view on "AI-based Modeling" with the principles and capabilities of potential AI techniques that can play an important role in developing intelligent and smart systems in various real-world application areas including business, finance, healthcare, agriculture, smart cities, cyber security and many more. We also emphasize and highlight the research issues within the scope of our study. Overall, the goal of this paper is to provide a broad overview of AI-based modeling that can be used as a reference guide by academics and industry people as well as decision-makers in various real-world scenarios and application domains.

Nowadays, we live in a technological age, the Fourth Industrial Revolution, known as Industry 4.0 or 4IR , which envisions fast change in technology, industries, societal patterns, and processes as a consequence of enhanced interconnectivity and smart automation. This revolution is impacting almost every industry in every country and causing a tremendous change in a non-linear manner at an unprecedented rate, with implications for all disciplines, industries, and economies. Three key terms Automation, i.e., reducing human interaction in operations, Intelligent, i.e., ability to extract insights or usable knowledge from data, and Smart computing, i.e., self-monitoring, analyzing, and reporting, known as self-awareness, have become fundamental criteria in designing today's applications and systems in every sector of our lives since the current world is more reliant on technology than ever before. The use of modern smart technologies enables making smarter, faster decisions regarding the business process, ultimately increasing the productivity and profitability of the overall operation, where Artificial Intelligence (AI) is known as a leading technology in the area. The AI revolution, like earlier industrial revolutions that launched massive economic activity in manufacturing, commerce, transportation, and other areas, has the potential to lead the way of progress. As a result, the impact of AI on the fourth industrial revolution motivates us to focus briefly on "AI-based modeling" in this paper.

Artificial intelligence (AI) is a leading technology of the current age of the Fourth Industrial Revolution, with the capability of incorporating human behavior and intelligence into machines or systems [95]. Thus, AI-based modeling is the key to build automated, intelligent, and smart systems according to today's needs. To solve real-world issues, various types of AI such as analytical, functional, interactive, textual, and visual AI can be applied to enhance the intelligence and capabilities of an application. However, developing an effective AI model is a challenging task due to the dynamic nature and variation in real-world problems and data. In this paper, we present a comprehensive view on "AI-based Modeling" with the principles and capabilities of potential AI techniques that can play an important role in developing intelligent and smart systems in various real-world application areas including business, finance, healthcare, agriculture, smart cities, cyber security and many more. We also emphasize and highlight the research issues within the scope of our study. Overall, the goal of this paper is to provide a broad overview of AI-based modeling that can be used as a reference guide by academics and industry people as well as decision-makers in various real-world scenarios and application domains.

Ethical AI:

AI ethicists have been formulating ethical principles and frameworks to responsibly guide the development and implementation of AI systems [97]. A key contribution came from who synthesized a set of core ethical principles like beneficence, non-maleficence, autonomy, justice, and explicability for cultivating a "Good AI Society." However, as principles alone they are in sufficient they need to be translated into concrete practices. Much work remains to develop these into practical tools and methodologies. Recent work has begun exploring approaches for embedding ethical values directly into AI system design, from which Value-sensitive Design (VSD) has emerged as a candidate to bridge the principle-practice gap. A recent critical review indicates that VSD may be effective but limited. Some limitations include the inadequate elicitation of values, a tendency to depend on pre-established values over context-specific ones, and a lack of precise instructions for embedding values.

AI Alignment:

Considering the potential for harm done by AI, some refer to such systems as misaligned with human values. For example, referencing social media, ethicist Tristan Harris says that by optimizing for attention, these platforms are misaligned with human wellbeing and dignity. "AI alignment" is a field of research that aims to develop systems that are aligned with human values and intent. Alignment has been earlier studied as the principal-agent problem in economics and law, where an agent must achieve the objectives and interests of the principal . For example, in a car repair scenario, the car owner (principal) expects the mechanic (agent) to fix the car efficiently and affordably. However, the mechanic might suggest unnecessary repairs to increase the bill (misalignment), contrary to the owner's desire for cost-effective service. Taking this framework to AI systems, alignment means ensuring that AI agents effectively and reliably pursue the goals and preferences set by their designers and users. One successful example of technical alignment work is the use of Reinforcement Learning with Human Feedback (RLHF) , which uses human preference data to align the behavior of Large Language Models (LLMs). Related techniques include Constitutional AI and inverse reinforcement learning (IRL). There are many new techniques in the expanding field of technical AI alignment.2However, while these technical efforts show tremendous progress, their technology-centered perspective risks missing broader sociotechnical considerations, such as the design of human systems to effectively respond to AI .

Why human-centered design?

Given the intrinsic relationship between wellbeing and conscious experience, some scholars have argued for the importance of human-centered design (HCD) in AI. One reason is that, as a field, HCD focuses on understanding and shaping human experiences. However, there are a variety of ways in which Human-centered design (HCD) might complement ethical perspectives and address gaps in the AI alignment field. For instance, HCD might help bring concrete implementation methods and a broader systemic perspective. A coretenet of HCD is to prioritize the needs, values, and capabilities of users, ensuring that the design process is centered around human beings and their interactions with technology. Designers are trained to attend to—and empathize with—human experiences. This means considering the full context surrounding users and technologies, rather than just narrow functionality, as well as prioritizing the understanding of diverse users' needs and experiences from their point of view. They are equipped with the ability to engage in stakeholder participation and reveal the ethical priorities and deeply-held beliefs relevant to design projects. This encompasses a blend of competencies from engineering design, including problem definition, scoping, and rapid prototyping, combined with methodologies from social sciences like conducting ethnographic research, interviews, deriving understanding from qualitative data, and engaging in empathetic practices. For a comprehensive overview, readers are referred to the live agenda summarizing ongoing alignment efforts posted to the AI Alignment Forum, which has been founded by prominent alignment researcher Eliezer Yudkowsky.

Positive AI: Key Challenges A PREPRINT:

These skills are particularly important for AI because the integration of diverse perspectives ensures that both technical efficiency and societal impacts are considered in AI development [98]. For instance, experimentation and prototyping in AI benefit from this blend, allowing for iterative refinement and alignment with human needs and values. Prototyping in AI can be difficult because of the inherent unpredictability and complexity in AI's capabilities and outputs . HCD may help by applying user-focused approaches to manage these uncertainties. Moreover, involving end users directly in the design process ensures that AI solutions are tailored to real-world requirements, making the technology more accessible, usable, and effective. In summary, the HCD perspective can complement existing ethical and technical viewpoints in AI development, as it offers methodologies to create systems that balance technical robustness with socially responsible outcomes that benefit people and society at large. The field of Positive Design focuses on promoting human flourishing. The Positive Design Framework provides ascaffold for solutions that can enhance subjective wellbeing through components like pleasure, meaning, and virtue. Grounding positive design in theory and evaluating its effect through controlled studies helps ensure that designed solutions truly contribute to people's happiness. Similarly, the Positive Computing Gaggioli, Riva, Peters, & Calvo, 2017) movement aims to leverage technology to measurably improve wellbeing and human potential. The emphasis on collaborations between fields like psychology, computerscience, and design in positive computing underscores the importance of an interdisciplinary, human-centric approach for developing AI focused on wellbeing objectives. In many ways, the tenets of positive design and positive computing have helped lay the foundation for what we now call "Positive AI."

Why wellbeing?

A growing movement of scholars advocates for the incorporation of wellbeing metrics into AI systems so that optimization efforts can measurably contribute to social benefit. Specifically, they argue that measures of wellbeing can help manage AI's effects on society. Indeed, wellbeing has a strong methodological foundation , and there is extensive research on defining and measuring wellbeing; this suggests that algorithmic systems may be able to systematically optimize wellbeing. Wellbeing's complexity captures many relevant societal concerns AI systems should address. This combination of rich meaning and inherent measurability supports the operationalizing wellbeing as an optimization objective for AI systems. This sentiment is also expressed by a recent IEEE standards review that argues for the adoption of holistic wellbeing frameworks (like IEEE 7010) to guide the design, deployment, and evaluation of AI systems. However, significant questions remain regarding whether available wellbeing frameworks are fully sufficient, whether existing metrics are sufficient, what the impacts of wellbeing optimization may be. Some argue that wellbeing is a sort of ultimate objective: in The Moral Landscape, S. Harris (2010) argues that other values like fairness, transparency, or accountability should be seen as components that contribute to wellbeing, rather than ends in themselves. From this perspective, optimizing for wellbeing involves optimizing for all values that matter, but only insofar as they contribute empirically to wellbeing. In so far as AI systems are able to assess their own impact on human wellbeing, they may be able to potentially maximize all benefits and minimize all harms experienced by users and society .Wellbeing optimization might then allow for the management of complex issues like misinformation and inequality associated with AI systems (Stray, 2020).

Framing the challenges: human-centered design of AI systems:

As a term, 'Artificial intelligence' is used to describe both a characteristic of computer systems and the methods employed to develop this feature, such as machine learning (ML) (Gabriel, 2020). Intelligence in both humans and machines has been defined as "an agent's general ability to achieve goals in a wide range of environments [99]." Following this definition, AI researchers Stuart Russel and Peter Norvig define artificial intelligence as a designed agent that perceives its environment through sensors and acts upon that environment using actuators. The result of these sensors and actuators is a feedback loop that incorporates system output (e.g., action in its environment) as input for its future actions (e.g., the action had the desired effect). A cybernetic perspective examines these broader feedback loops between AI systems, their environment, and the social context in which they operate. Thus, AI systems (in contrast to AI/ML algorithms) can be viewed as sociotechnical systems embedded within a complex network of feedback loops (van de Poel, 2020). This broader and more systemic view of AI has been proposed as an approach to deal with some of the challenges of current and future AI systems .

Key Challenges:

As experienced design researchers in this domain, we have consistently encountered unique challenges in designing Positive AI. The challenges we outline here are intended to inform and guide other designers embarking on similarventures.

I. Final Thoughts on AI's Role in Biology:

(a). Can Artificial Intelligence reach Human Thought:

The process of combining ingenious mathematical algorithms with extremely powerful computers allows scientists and engineers to focus with great precision on particular aspects of reality and to attain highly complex goals. The apogee of this process is reached with artificial intelligence (AI), which provides the next step in the hierarchy of great human endeavors that began with writing and printing and continued with computing and the internet.

Progress in AI and, in particular, the emergence of deep learning, coupled with the availability of powerful computers, have led to the surprising development that machines have defeated humans in a variety of games, starting with the triumph of IBM's Deep Blue, which in 1997 overpowered the chess champion Garry Kasparov.a The achievements of AI in chess, Go, and video games have been extensively publicized and, naturally, have created wide interest. However, the main reason for the excitement generated by AI is its success not in games but in a variety of real-life situations, which include the following: automatization of routine labor tasks, understanding of speech and images, and mechanization of certain medical diagnoses. There are many applications from voice, speech, text recognition and translation of a large number of languages, to protein folding, development of new antibiotics, and driverless cars.

The far-reaching achievements of deep learning, such as ChatGPT, have led several scholars to raise the question of whether AI can reach the level of "artificial general intelligence," namely, whether AI can reach and then surpass the level of human thought. The milestone where AI, supposing, reaches human intelligence was called by Vernor Vinge, the "singularity." This notion has been popularized by the futurist scholar and director of Google Engineering, Ray Kurzweil.

There is in my opinion a serious methodological problem concerning the possible proof that a machine has surpassed the human level of intelligence. This would require a proof that for every conceivable human goal, the machine achieves better performance. So far, this has been accomplished for particular goals by the direct competition of a human expert and a machine. For example, this happened for the goals of winning a chess or a Go game. However, it is apparent that such an approach cannot be used for an uncountable number of possible situations. Hence, unless a different methodology is suggested, the question of proving whether general AI has been reached is not well defined.

In any case, even if we assume that this question is well-posed, its analysis, necessitates, first, the introduction of a definition of intelligence. The cosmologist and leading AI exponent, Max Tegmark, attempted to provide such a definition. He defined intelligence as "the ability to accomplish complex goals." In his important book, Life 3.0: being human in the age of artificial intelligence, it is claimed that this definition encompasses Oxford Dictionary's definition of intelligence, "as the ability to acquire and apply knowledge and skills," as well as several of the definitions proposed in the Nobel Week Dialogue 2015: The Future of Intelligence. In this conference, among the definitions proposed for intelligence were, "the capacity for problem solving, learning, logic, and planning." According to Tegmark, acquiring knowledge, learning new information or a new skill, solving specific problems, employing logical algorithms, and designing concrete plans, can all be considered as processes subsumed by the phrase "accomplishing complex goals." It will be argued below, that although Tegmark's definition of intelligence is adequate for machines, it does not capture the essence of human thought. Indeed, I believe that this definition is appropriate for technology, which can be defined as a collection of devices and engineering practices as means of achieving a complicated goal.

(b)Automated high-throughput genome editing platform with an AI learning in situ prediction model:

Single nucleotide variations (SNVs) in the human genome may generate changes of transcription levels, protein sequences or many other properties of the original DNA, and cause genetic diseases. According to the ClinVar database of NCBI, more than 37,000 known diseases are associated with pathogenic SNVs[101]. The diseases caused by single nucleotide mutations include rare diseases, such as sickle cell disease, thalassemia, and Leber congenital amaurosis. A study by the European Organization of Rare Diseases has shown that more than 450 million people worldwide suffer from rare diseases, 95% of which remain without effective treatments to date. Even in some diseases with therapeutic solutions, patients usually require lifelong medicine while having low-quality life, and a shorter life expectancy.

The CRISPR/Cas9 technology is considered an ideal system to investigate and treat genetic diseases, infectious diseases, cancers, and immunological diseases. As a newer-generation CRISPR technology, base editors (BEs), enable direct, irreversible correction of base mutations, which have a promising future for curing genetic diseases caused by SNVs. Compared with standard genome editing, BEs can effectively repair base mutations without inducing double-stranded DNA breaks (DSBs), which reduce the occurrence of insertions or deletions (indels) at target sites. Three classes of base editors have been reported, including cytosine base editors (CBEs)that induce C•G to T•A conversion, adenine base editors (ABEs)that induce A•T to G•C conversion, and glycosylase base editors (GBEs) with C•G to G•C conversion.

These BEs provide almost ideal solutions for treating more than half of known pathogenic SNVs. However, before BE-based genetic therapies can be implemented, it is necessary to construct mammalian cell disease models for developing and optimizing BEs and enabling applications in gene therapy. Due to the great number of genetic diseases and known SNVs, it is necessary to develop a method that enables the construction of a large number of cell models carrying different pathogenic SNVs, so that extensive research on gene therapies can be performed to find curing solutions. According to ClinVar, approximately 50% of total human pathogenic SNVs are C•G to T•A conversion, which can be corrected by ABEs. However, it is currently hard to obtain large numbers of cell models carrying these SNVs with reasonable labor and funding investment.

Mammalian cell lines are usually used for developing and optimizing the BEs, and research for prediction of base editing performance, such as efficiency and specificity, requires a large amount of editing data [102]. To solve this problem, methods based on a target-locus integration library were developed, such as the Be-Hive, which provided the data for AI to learn and predict the editing performance. However, currently such data was obtained from integrated editing loci which lacked in situ information. Previous research has shown a strong correlation between the performance of nuclease and the chromatin accessibility properties. Kristopher et al. demonstrated that gene editing was more efficient in euchromatin than in heterochromatin. Large-scale genetic screens in human cell lines indicated that highly active sgRNAs for Cas9 and dCas9 were found in regions of low nucleosome occupancy, and the nucleosomes directly impeded Cas9 binding and cleavage in vitro. We previously found that pioneer factor, such as Vp64, improved CRISPR-based C-to-G and C-to-T base editing by changing local chromatin environment. However, current studies on deep learning employed the editing data from lentiviral integrated target sequences, while the real chromosomal environment of the target sequence was ignored. One of the reasons is that it is difficult to obtain a large set of editing data from endogenous target sites. For large scale samples, manual operations are not only time-consuming, but also error prone, less consistency and expensive. An automatic platform would make it possible to get large-scale editing dataset of endogenous targets. And with the large-scale in situ editing data and sequence information, combined with local chromatin accessibility, a machine learning model with in situ data might be able to better predict the actual base editing efficiency.

In this study, we devise an automated platform that performs the whole genome editing process from guide RNA (gRNA) design to the analysis of the editing results, which comprehensively characterizes the relationships of the in situ base editing outcomes with the sequence and chromatin environment for BEs.

(I). Conclusion:

Artificial Intelligence (AI) is a double-edged sword: on one hand, AI promises to provide great advances that could benefit humanity, but on the other hand, AI poses substantial (even existential) risks[96]. With advancements happening daily, many people are increasingly worried about AI's impact on their lives. To ensure AI progresses beneficially, some researchers have proposed "wellbeing" as a key objective to govern AI. This article addresses key challenges in designing AI for wellbeing. We group these challenges into issues of modeling wellbeing in context, assessing wellbeing in context, designing interventions to improve wellbeing, and maintaining AI alignment with wellbeing over time. The identification of these challenges provides a scope for efforts to help ensure that AI developments are aligned with human wellbeing. It is not a naturally observable quantity, but rather a multifaceted construct that is based, at least in part, on conscious human experiences. Therefore, designing Positive AI requires understanding and shaping human experiences. This situates the challenge squarely in the domain of human-centered design .Before reviewing the possibilities for HCD in designing AI for well-being, we will briefly address other fields associated with the creation of positive human outcomes in AI. The current article is not the venue for reviewing them in depth. Yet, we find it important that Positive AI designers are aware broadly aware of their contributions.

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