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DRUG RESEARCH AND DEVELOPMENT USING ARTIFICIAL INTELLIGENCE

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ABSTRACT

Artificial Intelligence simply called AI is a branch of computer science which uses computer programming languages to fix some problems. Now-a-days it widely evolved in the areas of Pharmacy, Health care, medicine. Etc. The field of computer science is increasing daily the applications of AI also increasing. Drug discovery and development takes much time and money. To create a small drug molecule it will takes billions of dollars. To reduce these problems AI was used in phamra industries. Drug development and discovery are increasingly relying heavily on AI. AI is used throughout, from the initial phase of target selection to the conclusion of marketing, saving time and money. In this review, deals about the different phases of drug discovery and development like target identification, protein- drug interactions, lead optimization, QSAR studies, molecular docking and virtual screening, clinical trails, Phytochemical screening, binding affinity, toxicity studies. In these, various AI applications uses were mentioned. Not only drug discovery process AI also used in different fields of pharma sectors.

KEYWORDS: Artificial intelligence (AI), computer science, drug discovery, drug interactions, target, lead, QSAR, docking, virtual screening, clinical trails.

INTRODUCTION

Artificial intelligence (AI) is the computer - generated simulation of the human intelligence process. Receiving information, formulating rules for interpreting the information, reaching approximate or definite conclusions, and self-correction are all part of the process.[1] Artificial intelligence (AI) is a multidimensional technology that enables people to reconsider how they combine information, analyse data, and use the resulting insights to better decision-making. It is already transforming all fields of human endeavour.[2]

History of AI

Table 1: Histroy of AI.

S.no	Scientist name	Contributions in developing AI	Ref
1.	Alan Turing	➢ Founder of AI ➢ Developed an imaginary computer of infinite memory in 1935. ➢ Used chess game to illustrate his theories. ➢ Turing award, an highest honorable award in the field of computer science.	[3,4]
2.	John McCarthy	➢ Father of AI ➢ Coined the term artificial intelligence. ➢ Created an Lisp, a programming language widely used in robotics, various scientific applications, variety of web-based services, detection of credit card fraud. ➢ Concept of cloud computing.	[4]
3.	Marvin Minsky	➢ Dartmouth Conference member. ➢ He collaborated with John McCarthy in 1959. ➢ artificial neural networks. ➢ Won Turing award in 1969.	[4]
4.	Allen Newell	➢ Logic Theory Machine. ➢ General Problem Solver. ➢ Won Turing award in 1975.	[4]
5.	Claude Shannon	➢ His paper ‘A Mathematical Theory of Communication.’ ➢ Natural language processing and computational linguistics.	[4]
6.	Nathaniel Rochester	➢ Designing IBM’s first commercial computer. ➢ Pattern recognition and intelligent machines.	[4]
7.	Geoffrey Hinton	➢ Geoff Hinton, along with Yoshua Bengio and Yann LeCun, is widely regarded as one of the "Godfathers of AI."	[4]

Artificial intelligence(AI) types

There are 4 types of AI(Artificial intelligence) are present. They are:

1. Reactive AI,
2. Limited memory
3. Theory of mind
4. Self-aware.[5]

1. Reactive AI

Reactive AI is the most basic form of AI; it is created to give a predictable result depends on the information that receives. Reactive robots are unable of learning actions or conceptualising the past or future, and they always react to events in precisely the same way each and every time.

Ex: Deep blue,[5,6] The Netflix recommendation engine, Spam filters.[5]

Although reactive AI constituted a significant advancement in artificial intelligence research, these AIs remain limited to doing the tasks for which they were originally designed. As a result, they are naturally restricted and open to development. Scientists constructed the following type of AI on this foundation.[5,6]

2. Limited memory

Limited memory AI develops practical information by observing behaviours or data, learning from the past. To make predictions and do challenging categorization tasks, this kind of AI mixes pre-programmed information with historical, observational data. This type of AI currently utilizing most.

Ex: self driving cars in now-a-days.[6] They watch the direction and speed of other vehicles. That cannot be accomplished in a single instant; rather, it calls for the identification of certain things and continuous observation of them.[5]

3. Theory of mind

Do you want to have an in-depth chat with an emotionally intelligent robot that duplicates human speech and appearance with theory of mind AI, that is imminent.

With the assistance of this type of AI, machines will achieve true, human-like decision-making abilities. Machines with theory of mind AI will be able to identify, evaluate, and remember emotional responses in order to adjust their behaviour while interacting with humans.[5,6]

4. Self-aware AI

Self-aware AI is the most sophisticated type of artificial intelligence. When machines are able to recognise both their own emotions and the feelings of those around them, they will be more conscious and intelligent like humans. Additionally, this type of AI will have needs, wants, and emotions.

Machines that use this type of AI will be able to recognise their own emotions and behavioral states. They will be able to make inferences that other AI can't, like "I'm feeling upset because somebody knocked me off in traffic."[5,6]

Drug discovery and development

Drug development and discovery are the two main components that make up the process of discovering and developing new drugs. The process of developing a chemical compound to

interact with a disease target after identifying and validating the target as a disease target is known as drug discovery. This interaction may serve to prevent, encourage, or otherwise alter the target's activity. Drug development includes fulfilling every prerequisite that must be completed before a novel molecule may be accepted for initial testing in human subjects.[7]

Phases of drug discovery and development include:

1. Target identification.
2. Target optimization.
3. Lead identification.
4. Lead optimization.
5. Pre-clinical evaluation.
6. Clinical trails.

1. Target identification

Discovering the biological origin of an disease and prospective intervention targets are the primary phase in the development of a new medicine. The process of finding potential treatment targets (genes, nucleic acids, or proteins) begins with determining each one's function and contribution to the disease.[8] Targets are naturally occurring cellular or molecular structures that are implicated in pathology and are accountable for disease; they can be receptors, enzymes, nucleic acids, hormones, ion channels, and so on.

In order to identify the target, The in-Silico approach is commonly employed in this field; it is a computer-based strategy for studying particular chemical changes in the body or targeted organism and designing a mixtures to meet a therapy profile.[7]

2. Target validation

Target validation is the procedure for verifying the wanted molecular target of a small molecule, such as a gene, protein, or nucleic acid. Target validation include identifying the structure activity relationship (SAR) of tiny chemical analogues, discovering a drug-resistant mutant of the suspected target, knocking down or over-expressing the presumed target, and monitoring the known signalling systems downstream of the presumed target. The process of proving the functional significance of the chosen target in the diseased phenomenon is known as target validation.

3. Lead identification

An appropriate chemical lead is a molecule which is active in 1^0 and 2^0 assays and as acceptable specificity, affinities, and selectivities for the target receptor. It must also be synthetically stable, practical, and drug-like. In order to do this, the structure–activity connection must be defined, the viability of a synthetic process must be identified, and there must be few preliminary evidence of in vivo evaluation and target activation.

4. Lead optimization

Follows to the identification of a 1^0 lead compound, a drug candidate is created via the lead optimization procedure. An iterative process of producing and characterization of a potential medicine is used to develop a picture of how its chemical makeup and activity relate to how it interacts with its targets and how it affects its metabolism.

The initial drug discovery process involves lead optimization, which identifies interesting compounds from the hit-to-lead high throughput screening test results. Lead optimization, the final phase of early stages drug discovery, involves evaluating promising leads for a number of traits, such as selectivity and binding processes. Lead optimization aims to enhance structural flaws in the lead element while preserving beneficial qualities in lead compounds.

5. Preclinical evaluation

As part of the drug development process, pre-clinical research examines a medicine's safeness and effectiveness on animal species with a view towards potential human outcomes. Additionally, the relevant regulatory authorities must approve pre-clinical investigations. Animal species like rats, mice, hamsters, rabbits. etc are used for experimental process under CPCSEA guidelines. By using this preclinical methods, the pharmacological and toxicological properties of drug identified.[8]

6. Clinical trials

Clinical trails are conducted on volunteer human subjects. To conduct clinical trails one should get approval from FDA by clinical trial registration.[9] In India, The registration was done on Clinical Trials Registry – India (CTRI) online.[10] All drug related activities are identified in clinical trials. There are 4 phases of clinical trials. They are:

i. Phase-1 (clinical pharmacological evolution)
ii. Phase-2 (Efficacy and side effects)
iii. Phase-3 (Efficacy and adverse drug reactions monitoring)

iv. Phase-4(Post-Market Drug Safety Monitoring)[8]

Artificial intelligence in drug discovery and development

One of the main goals of humans is to regulate these modifications for humans benefit. This is particularly true in the fields of medicine and pharmaceuticals, which are continually undergoing change.[11] Artificial intelligence (AI) has recently grown to be hot topic in the health care sector. The bio-pharmaceutical industry is attempting to usage of AI to improve drug discovery process to reduce research and development costs, clinical trial failure rates, and ultimately synthesize better medicines.[12]

Data digitization in the pharmaceutical industry has dramatically increased during the last few years. To answer challenging clinical problems, it is difficult to acquire, examine, and apply this knowledge as a result of digitalization.[13,14]

Target selection and validation

AI-enhanced technologies had developed into adaptable tools that can be used across all phases of drug development, which include the identification and validation of drug targets, the design of new drugs, drug re-purposing, the aggregation and analysis of biomedicine data, and the improvement of decision-making processes to enlist patients in clinical trials.[15,16] In addition, pharmacological qualities, protein characteristics and efficacy, drug combination and drug-target connection, and drug re-purposing are more applications of AI in the drug development process.[15]

Drug Information Bank (which includes drug substances, expression of gene, interplay between proteins, and records of clinical data) from public library is being analysed using AI to possibility for future treatment. As an instance, using modern engineering with the deep auto-encoder, free algorithm, and binary classification with the Xgboost algorithm on "genome-wide protein interaction network, drugs and their targets information" can result in scores for potential targets that can be used to enable target prioritisation.[17]

Algorithm for AI drug design Reinforcement Learning may be effectively applied to a string known as the "Simplified molecular input line-entry system," which is a specification for expressing chemical species using short ASCII(American Standard Code for Information Interchange) sequences. Potential energy measurements, molecular graphs with different

atom or bond weights, Coulomb matrices, molecular fragments or bonds, three-dimensional atomic co-ordinates, etc. are all included.[17]

AI might help pharmaceutical firms release drugs to the market more quickly. In addition to its spectacular gene-sequencing job, AI is also being taught to foresee therapeutic efficacy and adverse effects as well as to manage the enormous volumes of paperwork and data required to promote any pharmaceutical product.

A brief overview The phrase "artificial intelligence," or AI, is used to refer to a variety of cutting-edge computing approaches. Machine learning, which uses mentored pattern-matching and statistical analysis to identify trends or forecast outcomes, and natural language processing (NLP), which decodes human-written words to determine their meaning and can also create sentences that resemble human writing, are two that are important to pharma companies.[18]

Finding molecular targets or understanding the process with AI

The method of pathways or target discovery to cure diseases have changed as a result of AI's impact on drug development. This was made possible by the incorporation of genetic data, biochemical characteristics, and target tractability.[19] According to one study(Enrico Ferrero et al.,), animal prototypes expressing a disease-related gene with a neural network classification algorithm of grater than 71% reliability proffered the most predictive power when it came to forecasting therapeutic targets using the computational estimation programme "Open Targets," a platform containing gene-disease related information.[1,20]

AI in target protein structure prediction

Assigning the right target during drug molecule development is crucial for effective treatment. The development of the disease involves many proteins, some of which are over expressed. Therefore, it is essential to forecast the structure of target protein while designing the therapeutic molecule in order to selectively target disease. Because the design is in line with the surrounding environments of the target protein site, AI can help in structure-based drug discovery by anticipating the 3D protein image.[21] This aids in anticipating the impact of a compound on the target together with safety considerations before their synthesis or production. The 3D target protein structure was predicted using the DNN-based AI tool AlphaFold, which achieved good results by correctly predicting 25 out of 43 structures.[13]

In a report, a non-linear 3 layered NN toolkit based on a feed-forward supervised learning and back propagation error method was used with MATLAB to estimate the 2D form of a protein. The input and output data sets were trained in MATLAB, and the NNs served as learning algorithms and performance judges. Prediction of the 2D structure was accurate to 62.72%.[22]

AI in drug–protein interactions prediction

The effectiveness of a therapy is significantly influenced by drug-protein interactions. To fully comprehend a medication's efficacy and effectiveness, as well as to enable drug repurposing and avoid polypharmacology, it is crucial to forecast how it will interact with a macro-molecule or protein. In order to improve therapeutic efficacy, many AI techniques have been helpful in the precise forecast of ligand-protein reactions.[23] Depending on original protein sequences and the structural properties of tiny molecules, in one method(Wang et al.), produced a prototype utilising the SVM (Support vector machines) method that was mentored on 15,000 protein-ligand reactions. This model was used to find 9 new compounds and their interactions with 4 important targets.[24] Drug-protein interactions are predicted using FINDSITEcomb. Estimates using a average of 329 human targets for every medication indicated more disruption.[25]

AI in In-silico drug design

AI for QSAR

An computer generated method depends on the quantitative structure-activity relationship (QSAR) may quickly anticipate a large number of chemicals or basic physicochemical properties like log P or log D. However, these models are far from the capacity to anticipate complicated biological features like a compounds efficiency and unfavourable adverse effects. Additionally, QSAR-based models have issues with short training sets, incorrect experimental database in training sets, and a shortage of experimental validation.

To address these issues, large data modelling and analysis based on recently established AI methodologies, like DL (Deep learning) and pertinent modelling studies, can be used to evaluate the safety and effectiveness of pharmacological compounds. In order to examine the advantages of DL in the drug development process in the pharmaceutical business, Merck launched a QSAR ML (machine learning) challenge in 2012. In 15 drug candidate-related absorption, distribution, metabolism, excretion, and toxicity (ADMET) data sets, DL models outperformed conventional ML methods in terms of forecasting.[26,27]

The development of AI-based QSAR techniques, which includes linear discriminant analysis (LDA), support vector machines (SVMs), random forest (RF),[28,29] and decision trees, has allowed for the use of QSAR modelling tools for the discovery of new therapeutic candidates.[28] When compared with the capacity of 6 AI algorithms to rank unidentified compounds in terms of biological action with that of conventional methods, King et al., mentioned a minimal statistical difference.[30]

AI in molecular docking and virtual screening

Molecular docking is one of the most utilised computer techniques to study these interactions. By inserting every substance from a compound library into a specific area of a target receptor with an understood 3D structure, Docking-based Virtual Screening (DBVS) enables the identification of more powerful ligands. Janaina Cruz Pereira et al., taken an experiment in that they compare the results of using application deep VS. In this, they compare deep VS and autodock vina, deep VS-Dock and deep VD-ADV. 40 receptors and 2950 ligands are used.[31]

AI in Lead optimization

The most costly and time-consuming stage of drug research is lead optimization (LO). It is a multi-parameter optimization (MPO) problem at its core, with the objective of finding molecules with the best combination of drug-like qualities while retaining adequate potency. Finding this midpoint is difficult because it calls for simultaneous optimization of several, frequently conflicting goals, including potency, safety, specificity, efficacy, and pharmacokinetics (PK) features.

The design-make-test-analyze (DMTA) cycle is repeated iteratively during the LO process, therefore cutting down on the no.of iterations is essential for expediting the LO process. AI-guided generative modelling used in generative chemistry has shown success in lowering the number of iterations and creating compounds that fulfil the specified LO criteria. AI is also progressing in the field of computer-aided synthesis planning (CASP), which is useful for identifying hits and enhancing DMTA cycle effectiveness.[32]

Lead optimization was done by using naive Bayesian classifiers, k-nearest neighbours, and artificial neural networks applications of AI.[17]

Clinical trails using AI

Clinical trials take about 6-7 years to complete and include a substantial financial outlay in order to determine the safety and effectiveness of a medicinal product in people for a specific illness condition. Only one out of every ten molecules that undergo these trials, though, are cleared successfully, which is a huge loss for the industry.[33] These failures may be the result of bad infrastructure, poor technical prerequisites, and poor patient selection. With the help of AI, these problems can be minimised because to the abundance of digital medical data that is already available.[34]

One-third of the time required for a clinical trial is spent on patient enrollment. The enrollment of suitable participants can prevent the 86% of clinical trials that fail that would otherwise occur from occurring.[35]

The AiCure smartphone app employs aggressive AI technology to monitor medication compliance in a Phase II experiment involving subjects. It was asserted that AiCure increased adherence by 25% when compared to the standard "modified directly observed therapy." With the application of AI predictive modelling in patient population selection, clinical trial success rates would increase.[36]

AI IN PREDICTION OF DRUG PROPERTIES

Phytochemical screening

When creating a new medicine, physicochemical characteristics including solubility, partition coefficient (logP), degree of ionisation, and intra-cellular permeability must be taken into account because they have an indirect impact on the drug's pharmacokinetics and target receptor family. It is possible to anticipate physicochemical properties using a variety of AI-based methods. For instance, ML trains programmes using huge data sets generated during earlier compound optimization. Molecular descriptors, such as SMILES strings, potential energy measurements, electron density around the molecule, and coordinates of atoms in 3D, are used in drug design algorithms to produce viable molecules via DNN (deep neural network) and afterwards forecast their attributes.[13]

Binding effinity

The binding location of the receptor would be known in various therapeutic and targeted drug-design uses. The binding site has yet to be identified in several applications, though. In the early 2000s, a Canadian/German group developed a neural network algorithm that can

recognise binding sites in receptors by grouping fragmented, overlapping patches into 1 of 4 protein-binding types: protein (which include proteins and peptides with more than 8 amino acids); DNA (which includes DNA and RNA); ligand (which include anything that is not in the other classes); or non-binding.[37]

AI-Bind is an application used for enhance the predictions of new proteins and ligands' binding.[38] DeepSite employed AI to predict the druggability at protein binding sites based on pictures.[39] Pertaining to exact and repeatable binding affinities utilised in ML. The models are thermodynamic integration with enhanced sampling (TIES) and enhanced sampling of molecular dynamics with approximation of continuum solvent (ESMACS).[37] Following the stage of molecular docking, eSimDock is yet another technique to forecast binding affinities.[40]

Solubility

One of a drug's most crucial properties in medical chemistry is solubility. According to Boobier et al., ML and human estimates of solubility for organic compounds that are similar to drugs are both accurate. Such outcomes lend legitimacy to the application of ML, particularly if the time and resources needed are affordable.[41]

In order to create COSMO-RSol, Klamt et al. combined the conductor-like screening model (COSMO) with ab initio electronic structure theory, such as density functional theory (DFT). In addition to liquid-liquid and liquid-vapor states (like COSMO-RS), COSMO-RSol seeks to predict the equilibrium constants for solid states as well by accounting for the energy of fusion.[37,42]

Toxicity

To prevent hazardous effects, it is essential to know how poisonous any medicine molecule is. The cost of developing new drugs is increased by the frequent use of cell-based in vitro assays as preliminary investigations, followed by animal trials to find out compounds toxicity. Several web-based programmes are available to help lower the cost, including LimTox, pkCSM, admetSAR, and Toxtree.[43] Acute (one-time) or repeated exposures at varied doses and intake methods can be used to determine the toxicity. TOXNET, ToxCast, Tox21, PubChem, DrugBank, ToxBank Data Warehouse, ECOTOX, and SuperToxic are some of the current toxicity databases.[44] OpenTox (opentox.net) is one of the notable open platforms for in silico toxicity forecast.[45]

Advanced AI-based methods predict a compound's toxicity based on input features or explore for commonalities between substances. The US Food and Drug Administration (FDA), the Environmental Protection Agency (EPA), and the National Institutes of Health (NIH) jointly launched the Tox21 Data Challenge to test so many computer methods for predicting the toxicity of 12707 pharmaceuticals and environmental chemicals.[43] An ML algorithm called DeepTox outperformed all competing methods and was able to precisely identify the toxicity of a molecule based on predetermined 2500 toxicophore features by characterising both static and dynamic features within the chemical descriptors of the molecules, such as molecular weight (MW) and Van der Waals volume.[46] The complex tissue metabolism simulator (TIMES) model incorporates more toxicity "theory." It takes into account the metabolic processes that, after particular metabolic transformations, may detoxification of drug compounds.[47]

DeepTox (determines the toxicity of new medications), and PrOCTOR (determines the likelihood of harmful effects in clinical trials) are platforms for AI that cananticipated consequences both on and off-target and in vivo safety profiles of compounds before they are synthesized. Another AI technology called Read-Across Structure-Activity Relationships (RASAR) may accurately forecast the toxicity of unidentified compounds by tying together molecular structures and hazardous features by searching a large chemical library.[15,48]

Table 2: different AI used in different phases of drug discovery phases.

S.no	Drug discovery and development phases	AI used
1.	Target selection and validation:	Xgboost algorithm, natural language processing (NLP).
2.	Finding molecular targets	Open Targets
3.	Target protein structure prediction	AlphaFold, MATLAB.
4.	Drug protein interactions prediction	SVM (Support vector machines), FINDSITEcomb.
5.	QSAR	DL (Deep learning), QSAR ML (machine learning), linear discriminant analysis (LDA), support vector machines (SVMs), random forest (RF), decision trees.
6.	Molecular docking and virtual screening	deep VS, deep VS-Dock, deep VD-ADV
7.	Lead optimization.	Bayesian classifiers, k-nearest neighbours, artificial neural networks.
8.	Clinical trails.	AiCure
9.	Phytochemical screening.	DNN (deep neural network).
10.	Binding effinity.	AI-Bind, DeepSite, thermodynamic integration with enhanced sampling (TIES) and enhanced sampling of molecular dynamics with approximation of continuum solvent

		(ESMACS), eSimDock.
11.	Solubility.	COSMO-RSol, density functional theory (DFT).
12.	Toxicity	Tox21, Deep Tox, tissue metabolism simulator (TIMES), PrOCTOR, Read-Across Structure-Activity Relationships (RASAR).

Applications of AI in pharmaceutical industries

AI in Pharmaceutical product development

The sequential addition of a new drug substance into an appropriate dosage form with the preferred delivery properties is necessary. The traditional method of trial and error can be replaced in this area by AI. Integrated expert Systems (ES) and ANN were used to produce a hybrid approach to development of Piroxicam direct-filling hard gelatin capsules in compliance with the specifications of its dissolution profile. Based on the input parameters, the Model Expert System (MES) decides and suggests changes to the formulation. In contrast, ANN makes formulation development simple by using back propagation learning to connect formulation parameters to the intended response, which is collectively regulated by the control module.[13]

The effectiveness of the powder's flow property on the die-filling and tablet compression process has been investigated using a variety of mathematical tools, including computational fluid dynamics (CFD), discrete element modelling (DEM), and the Finite Element Method.[49]

AI in Pharmaceutical manufacturing

The innovative Chemputer platform, which incorporates diverse chemical codes and uses the Chemical Components scripting language, aids digital automation for the preparing and manufacture of molecules.[50] Sildenafil, diphenhydramine hydrochloride, and rufinamide have all been successfully synthesised and manufactured using it, and the yield and purity are noticeably similar to those of manual synthesis.[51]

AI tools like the meta-classifier and tablet-classifier are used to control the final product's quality standard and to flag any manufacturing errors in tablets.[52]

AI in Quality assurance

The quality assurance of the drug can be ensured using an automated data entry platform, such as an Electronic Lab Notebook, and sophisticated, intelligent approaches.[53]

AI in pharmaceutical product management

AI in market positioning

Technology and e-commerce are platforms have made it simpler for businesses to establish a brand's natural awareness in the public sphere. As revealed by the Internet Advertising Bureau, businesses use search engines as one of the technology platforms to hold a prominent place in online marketing and aid in the positioning of the product in the market. Businesses consistently strive to rank their websites higher than those of rival businesses in order to quickly gain recognition for their brand.[54]

A deeper understanding of markets was offered by other tools, including statistical analytic techniques and particle swarm optimization algorithms (introduced by Eberhart and Kennedy in 1995). On the basis of a precise forecast of customer demand, they can assist in choosing the marketing strategy for the product.[55]

AI in market prediction and analysis

Using prediction tools, AI assisted in the thorough examination of a product's essential requirements from the perspective of the client as well as in understanding the needs of the market. Additionally, it may study the market and forecast sales. AI-based software displays adverts that, with just one click, take users to the product's website, enticing them to buy and raising awareness among doctors.[56]

Many business-to-business (B2B) firms have unveiled technology for self-service that provide free browsing of health items, which can be quickly located by providing their specifications, as well as the ability to place orders and track their delivery. To address the unfulfilled requirements of patients, pharm industries are also launching their web applications, such as 1 mg, Medline, Netmeds, and Ask Apollo.[57]

AI in product cost

The software analyses enormous quantities of statistical data, including drug development price, market require, inventory costs, production costs, and rivals' product prices, and then creates algorithms for estimating the product price. AI tools like Intelligence Node's (established in 2012) In competitor, a full-featured retail competitive intelligence platform, analyse competitor pricing data and assist businesses and retailers in keeping track of the competition. By allowing users to choose their own prices for their products, Wise Athena

and Navetti PricePoint believe that pharmaceutical businesses can utilise the same tools to help with product pricing.[13]

Application of AI tools in different fields

IBM Watson for oncology

Watson is a supercomputer invented by IBM that mixes artificial intelligence (AI) with advanced analytic tools to primarily provide answers to queries. To help oncologists make better decisions on the cure of cancer, Watson for Oncology was created. It functions by evaluating a patient's medical data using a wide network of data and expertise, then offering therapy alternatives depending on the information discovered. Watson for oncology can examine the context and significance of any data found in clinical notes or reports, whether they are correctly structured or not. It may quickly gather important data about the patient and express it in straightforward English, which can prove to be a crucial step in giving the patient the best possible treatment plan.[58,59]

Robot pharmacy

UCSF Medical Center uses robotic modeling for the manufacture and monitoring of pharmaceuticals with the aim of enhancing patient safety. They claim that the technology has properly manufactured 3,50,000 doses of medication without any mistakes. The robot has shown to be significantly better than humans in terms of size and its capacity to administer precise drugs. The production of oral and injectable medications, including hazardous chemotherapy agents, is one of the capabilities of robotic technology. The UCSF nurses and pharmacists now have more freedom to focus on providing direct patient care and collaborating with doctors in order to make the most of their knowledge.[58]

MEDi robot

Medicine and Engineering Designing Intelligence is abbreviated as MEDi. The community health sciences professor at the University of Calgary in Alberta, Tanya Beran, served as the project leader for the creation of the pain management robot. Aldebaran Robotics's MEDi can speak 20 different languages, has facial recognition technology built in, and is extremely adaptable to various settings. The robot establishes a bond with the kids before explaining what would happen during a medical treatment. It provides instructions on what to do, how to breathe, and how to manage during the medical treatment. Although the robot is incapable of thought, planning, or reasoning, it can be taught to exhibit AI.[60]

Erica robot

A researcher at Osaka University named Hiroshi Ishiguro created the new care robot Erica in Japan. It was created in cooperation with Kyoto University, Japan Science and Technology Agency, Advanced Telecommunications Research Institute International (ATR). It has a combination of European and Asian face traits and speaks Japanese. It enjoys watching cartoon movies, wants to go to Southeast Asia, and desires a living companion who will converse with it, just like any other typical human being. The robot was created with the ability to analyze and respond to inquiries with similar to human facial movements, but it cannot freely move. As a result of Ishiguro adjusting the attributes of 30 attractive women and using the average to construct Erica's nose, eyes, and other features, she is the "most beautiful and intellectual" android.[58,61]

TUG robots

The TUG autonomous robot moves supplies and materials throughout hospital around-the-clock. It keeps hospital team concentrated on patient care, offers extra capacity during times of high demand, and boosts logistical effectiveness as a whole. TUG completes tasks that people either shouldn't or don't want to complete. It helps all departments that are present in hospital i.e., Nursing, Pharmacy, Lab and food services. It carries all equipment's and food.[62]

CONCLUSION

Human beings are the most advanced machines ever made. Everyone are working together but today the world is changed. The Artificial intelligence(AI) which are created to reduce the risk. Now AI also used in Pharmaceutical industries. Many Pharma companies in now-a-days directly or indirectly they are depends on AI. In drug discovery and development AI plays crucial role for identifying and optimizing targets and leads. It reduces the cost and saves money. AI used from the begining of target identification to marketing the drugs. Not only in pharma industries AI is used in different fileds like Oncology. In hospitals AI tools are used like MEDi robot, Erica robot, TUG robot. etc. Artificial intelligence changing the procedure and time required for drug discovery. In future their is chance of discovering medicines or drugs quickly.

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