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Role of Artificial Intelligence in drug development

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ABSTRACT

In the last decade, artificial intelligence (AI) has revolutionised the field of drug research. Staff abilities (55 percent), data structure (52 percent), and resources were all factors in AI deployment (49 percent). Nearly 60% of respondents said they expected to hire more people in the next two years to assist AI usage or adoption in drug development. AI in areas like as drug research and development, drug repurposing, boosting pharmaceutical productivity, and clinical trials, among others, minimises human effort and allows for the achievement of objectives in a short amount of time. On the one hand, AI techniques used in drug development bring the drug development process and the use of various models closer to medicinal chemists, while on the other hand, AI methods used in drug development bring the drug development process and the use of various models closer to mathematicians

Keywords: Artificial intelligence; drug development; machine learning; deep learning and predictions.

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INTRODUCTION

Artificial intelligence (AI) refers to a computer's or a robot's ability to do tasks that would typically need human intelligence and judgement. Drug development is the process of bringing a new medicine molecule into clinical use. At various stages of the drug development process, AI has been used to discover novel targets [1], increase knowledge of disease processes, and produce new biomarkers, among other things. Many pharmaceutical companies have begun to invest in resources, technology, and services, notably in the development and compilation of datasets for AI research, such as machine learning and deep learning. It is represented as in Figure 1.

AI now plays a significant role in drug research, and several corporations have developed in-house efforts or formed collaborations with AI firms. AI is currently being used by certain firms to repurpose pharmaceuticals and uncover new uses for existing drugs and late-stage medicinal prospects. Drug development is the process of bringing a new drug molecule into clinical practice; in its broadest definition, it includes all stages from the basic research of finding a suitable molecular target to large-scale Phase III clinical studies that support the commercial launch of the drug to post-market pharmacosurveillance and drug repurposing studies.[2] A posture is generally created, graded, and compared to the previous pose during computational docking (s) through AI. There are several docking systems available for virtual screening, each with its own sampling process, scoring algorithms, ligand and receptor flexibility treatment, and CPU time necessary to dock a molecule to a specific target.

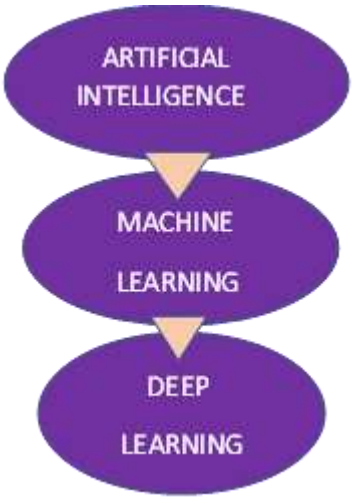

Figure 1: Learnings for drug development

AI in pharmaceutical products: Given that AI can aid rational drug design,[3] assist in decision making, determine the right therapy for a patient, including

personalized medicines, and manage clinical data generated and use it for future drug development.[4] AI can be expected to play a role in the development of pharmaceutical products from the bench to the bedside. Additionally, pharmaceutical businesses may use AI in the manufacturing process to increase productivity, efficiency, and speed up the creation of life-saving pharmaceuticals. All areas of the manufacturing process, including quality control and predictive maintenance, may benefit from AI. The AI in pharmaceutical product are mentioned in Figure 2.

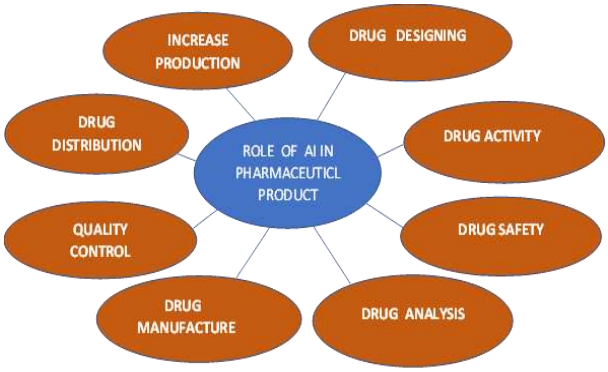

Figure 2: Role of AI in pharmaceutical product

AI in drug discovery: Researchers examine the interactions between different chemicals, genes, and proteins to identify which ones have the greatest promise, with the objective of uncovering novel targets, biomarkers, and compounds. RWD apps can help with some of these objectives. Deep learning has seen a late renaissance of interest in drug development, which has already resulted in an unparalleled burst of innovative modelling techniques and applications.AI can distinguish hit and lead compounds, allowing for faster therapeutic target validation and structural design optimization.[5]

AI in drug development: The subsequent inclusion of a novel drug molecule into a suitable dosage form with desirable delivery properties follows the discovery of a novel therapeutic molecule. In this case, AI can take the role of the previous trial-and-error method[6]. According to the FDA's definition the drug development process is divided into four parts. that are shown below in Figure 3. Drug discovery is the process of discovering novel therapeutic drugs by studying disease processes and molecular molecule characteristics (or other technologies). Clinical research: several stages of clinical trials to test the new treatment on people to determine its safety and efficacy; and post-marketing research: pharmacosurveillance and comparative effectiveness studies

Machine learning in drug development: Warren Mcculloch created the first artificial intelligence in 1949, where AI includes machine learning.[7] Artificial intelligence (AI) is a broad term that refers to computer programmes that can think and act like humans, whereas machine learning (ML) is a subset of AI in which data is fed into the machine along with algorithms such as Nave Bayes, decision trees (DT), hidden Markov models (HMM), and others that allow the machine to learn without being explicitly programmed. Later, with the invention of neural networks, robots were able to classify and arrange data in a way that was similar to that of a human brain, demonstrating additional improvement in AI. By designing a checker-playing software for IBM in 1952, Arthur L. Samuel popularised the phrase "machine learning".[8] Machine learning, in basic terms, is an area of artificial intelligence that is widely characterised as a machine's capacity to replicate intelligent human behaviour. Machines that can detect a visual picture, comprehend a text written in natural language, or perform a physical activity are examples.

Figure 3: AI in drug development

Machine learning classification: ML either utilises supervised learning, in which the model is taught to use labelled data, in which the input has been tagged with preferred output labels, or unsupervised learning, in which the model is trained to use unlabelled data but looks for recurrent patterns in the input data.[9] Others include semi-supervised learning, which combines supervised and unsupervised learning; self-supervised learning, which is a special case, employs a two-step process in which unsupervised learning generates labels for unlabelled data with the ultimate goal of creating a supervised learning model; and self-supervised learning, which is a special case, employs a two-step process in which unsupervised learning generates labels for unlabelled data with the ultimate goal of creating a supervised learning model. Finally, DL is a brain-inspired family of algorithms that mimics the human brain but requires high computational power for training and big data to succeed.[10] Reinforcement learning is a type of ML that improves its algorithm over time with the help of a constant feedback loop, and finally, reinforcement learning is a type of ML that improves its algorithm over time with the help of a constant feedback loop. The machine learning classification was mentioned in below Figure 4.

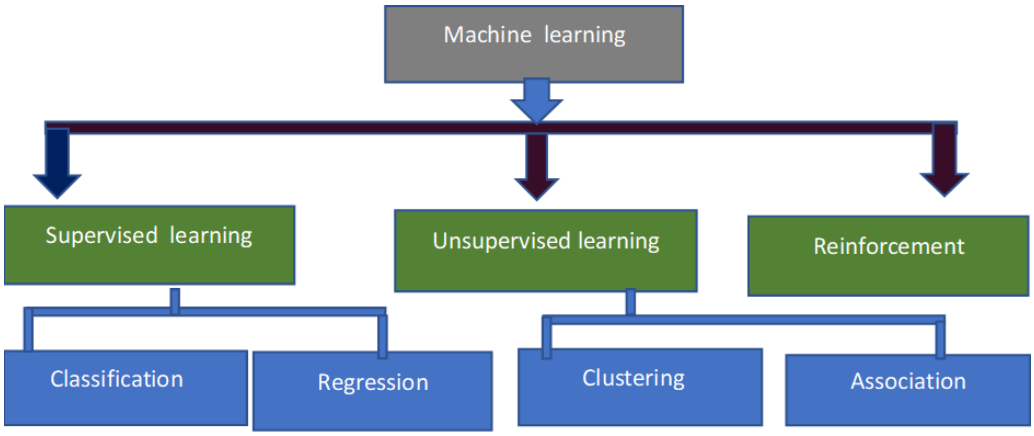

Figure 4: Machine learning classification

Deep learning in drug development: In 2017, the first FDA-approved cloud-based DL application was released, marking the first-time artificial intelligence was used in healthcare. In 1986, David Rumelhar, Geofrey Hinton, and Ronald J. Williams published "Learning Representations by Back-propagating Errors," demonstrating that backpropagation might help in form identification and word prediction [11]. There were several failures after the first breakthrough, but Hinton persevered over the second AI Winter to reach new heights. As a result, he is known as the Godfather of DL. Yann LeCun, at Bell Labs, presented the first practical demonstration of back propagation in 1989. AI algorithms such as ML to DL have been used more in computer-aided drug creation as technology has progressed and high-performance computers have been developed (CADD). The ambition of chemists to precisely foresee chemical activity-structure connections is not a novel strategy for scientists in drug discovery and development.

Rethinking of drug design: Despite breakthroughs in disease biology and great technological leaps, getting new medications to market remains a time-consuming and expensive procedure, due to the significant expenses involved with the high number of clinical trial failures.[12] To be long-term effective, AI-assisted medication design must answer multiple problems, which may be summarised as five "grand challenges." They're producing and getting suitable data, developing new hypotheses, optimising in a multi-objective manner, reducing cycle durations, and changing the research culture and attitude.

Traditional computational drug design through artificial intelligence: Computational approaches have played an important role in drug design and discovery for many years, transforming the entire process. Traditional computational approaches, on the other hand, are still connected with various concerns such as time cost, computational cost, and dependability.[13] Furthermore, de novo drug design has benefited from AI in recent years. For example, have developed MolAIcal (https://molaical.github.io/), a platform for designing three-dimensional medicines in three-dimensional protein pockets. [14]

Prediction of the physicochemical properties: Physicochemical features of a medication, such as solubility, partition coefficient (log P), degree of ionisation, and intrinsic permeability, have an indirect impact on its pharmacokinetic qualities and target receptor family, and must be taken into account when developing a new drug.[15] To predict the solubility of compounds, DL approaches such as undirected graph recursive neural networks and graph-based convolutional neural networks (CVNN) have been utilised. As a result, AI plays an important role in drug development, predicting not just the medication's desirable physicochemical qualities, but also its desired bioactivity.

Prediction of bioactivity: AI-based approaches can assess a medication's binding affinity by looking at the traits or similarities between the drug and its target. To identify the feature vectors, feature-based interactions recognise the chemical moieties of the medication and the target. In a similarity-based interaction, on the other hand, the similarity between the drug and the target is taken into account, and it is expected that comparable medications would interact with similar targets. Unsupervised machine learning approaches, such as MANTRA and PREDICT, may be used to predict the therapeutic efficacy of medications and target proteins of known and undiscovered pharmaceuticals, with implications for drug repurposing and understanding the molecular mechanism of therapies.

Prediction of toxicity: The project "Toxicity Testing in the Twenty-First Century" attempts to develop more efficient and effective ways for predicting how chemicals affect human health. Chemical compounds were provided in SDF format, which includes undirected, labelled graphs with nodes and edges representing atoms and bonds, respectively. In order to create suggestive features, Deep Learning thrives on enormous volumes of training data. well-performing models were classed (i.e., labelled) as "active,"

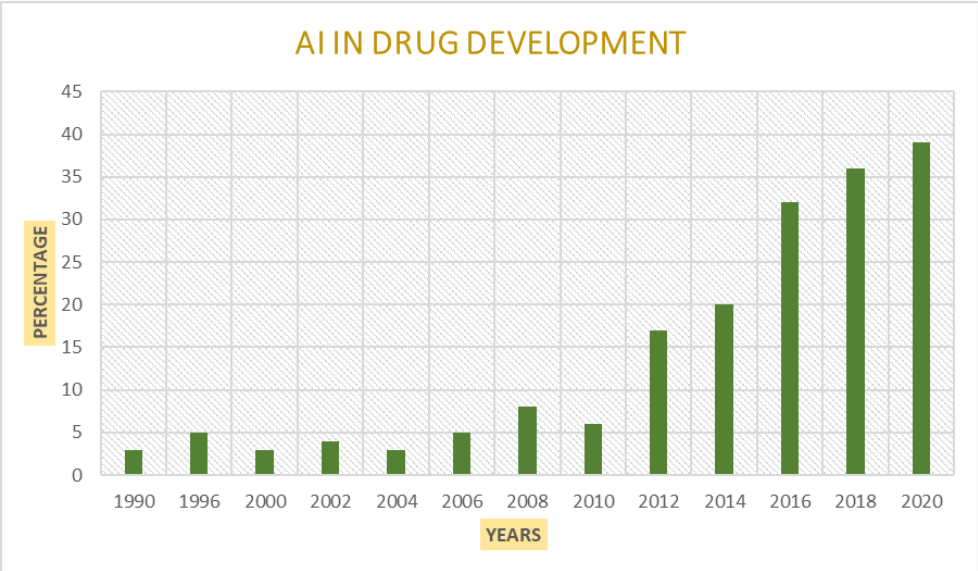

Figure 5: AI in drug development

"inactive," or "inconclusive/not tested" based on the results of the measurements. The availability of high-throughput toxicity testing has recently provided enough data for deep learning to be used for toxicity prediction.[16]

Virtual screening: Virtual screening (VS) is a supplementary technique to experimental HTS in which high-performance computers is used to analyse massive databases of chemical compounds to discover potential drug candidates.[17] Virtual screening is knowledge-based, which implies that some information about the nature of the receptor binding pocket, the type of ligand expected to bind effectively, or both, is accessible.

The type of method(s) used in VS is determined by the information provided as input and the type of output required. If a 3-D structure of the target protein is known, for example, molecular docking or combinatorial drug design can be utilised to sieve receptor-based, fine-grained molecules. If a 3-D receptor structure is not available, VS can employ a pharmacophore model built from bioactive ligands or molecular property profiles like molecular weight, lipophilicity, ADME characteristics, or drug-like qualities as filters.

Docking: The study of molecule-to-molecule interaction is known as molecular docking. Search techniques based on Monte Carlo, evolutionary algorithms, fragment-based, and molecular dynamics are among the most widely used docking approaches. Computational docking of a tiny molecule to a biological target entail sampling a large number of alternative poses for the former in the given binding pocket of the latter in order to find the best binding geometry, as determined by a user-defined fitness or scoring function. For protein and nucleic acid targets, X-ray crystallography and NMR spectroscopy remain the key sources of 3-dimensional structural data.[18]

Representation of ai in drug development: The introduction of a novel medicine to the commercial market is a complicated and lengthy procedure that normally takes several years and involves significant financial expenses due to a high attrition rate. As a result, there is a pressing need to optimise this process employing cutting-edge technology like artificial intelligence (AI) (Figure 5). The FDA has recently advocated for the use of real-world data (RWD) in medication development.[19] RWD refers to information gathered from sources other than traditional research settings, such as electronic health records (EHRs), administrative claims, and billing data [20]. Few studies employed AI on RWD at various stages of drug development, with the majority occurring in the clinical or post-marketing periods. Trial recruitment optimization, adverse event identification, and medication repurposing were the three primary types of studies that applied AI on RWD. According to one estimate, AI was employed by 68 percent e39 percent of the pharmaceutical sector.

Future scope: AI algorithms learn on data, and the availability of databases for training determines the quality of the outcomes. Drug design presents a number of difficult difficulties in terms of information selection, data modelling, classification, prediction, and optimization, all of which encourage the development and use of specialised AI systems. Artificial intelligence (AI) is being used to detect links between patterns of genetic variants and expression profiles and clinical and other phenotypes, as well as to create predictive fingerprints of disease states, progression, and therapeutic intervention outcomes. CTS studies employ computational simulation approaches on selected populations to evaluate alternative trial designs before investing money in the real clinical trial.[21] The majority of respondents (59%) said their company planned to hire more people to help with AI installation or use in the next two years.

Limitations: Datasets are used to train AI models. As a result, if the training dataset is insufficient, bi assed, or unequally distributed, the AI model's function will be harmed, and the task outcomes it provides will be prone to errors. AI developers should collaborate with medical practitioners, ethicists, and philosophers to address ethical challenges in terms of ethical principles while employing AI.[22] To take hold of this, regulations should be devised in this direction. Because it contains misspellings, non-medical terms and slang, duplicates due to multiple postings, incomplete data due to missing important information, a lack of standards, a large volume of data, and a high signal-to-noise ratio, using social media safety data by an AI has its own set of limitations (only a small proportion of drug safety data collected from social media contains information associated with ADRs). The International Council for Harmonization of Technical Requirements for Pharmaceuticals for Human Use (ICH) has issued standards for tracking AI in medication safety.

CONCLUSION

Over the last five years, contemporary AI approaches have matured to the point that they may be used in medical and healthcare settings. The growth of AI, along with its astonishing tools, is constantly aimed at reducing obstacles faced by pharmaceutical firms, affecting the medication development process as well as the total lifespan of the product, which might explain the rise in the number of start-ups in this field. Personalized pharmaceuticals with the necessary dose, release characteristics, and other needed elements may be made according to each patient demand by using AI into pharmaceutical product production.

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