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REVIEW ON ARTIFICIAL INTELLIGENCE IN DIFFERENT MEDICAL FIELD

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ABSTRACT

Artificial intelligence's usage in pharmaceutical technology has grown in recent years, and it can save time and money while also improving understanding of the links between various formulations and process parameters. Artificial intelligence (AI) is a discipline of engineering science concerned with the development of intelligent computers. Neural networks and perceptrons are used in the creation of intelligent devices. Artificial neurons learn, solve problems, and make decisions in the same way that humans do. This study focuses mostly on AI milestones as well as the AI system's benefits and drawbacks. In all sections of the healthcare system, the applications of AI systems in the drug discovery process and formulation types were thoroughly addressed.

KEYWORDS: Digital learning, Pharmacy, Network, Learning.

INTRODUCTION

The computerization of human intelligence is known as Artificial Intelligence (AI). Data collection, usage guidelines, preliminary or definite results, and self-correction are all part of it. Many people are concerned that AI would jeopardize their jobs; however, every innovation in AI is viewed as vital in terms of societal advancement.[1] Disease diagnosis, monitoring, comprehension, driving autos, trading currencies, and other medicinal chemistry operations could all benefit from Artificial Intelligence. In silico analysis can help with almost any subject that requires the detection of patterns and the discovery of relationships in large datasets.[2] Artificial Intelligence (AI) is becoming more widely used, notably in the pharmaceutical business.[3] Long and expensive medicine development cycles, as well as consumer and legislator price expectations, dominate the existing pharmaceutical infrastructure.[2,3] Artificial Intelligence is being employed in the pharmaceutical sector for

therapeutic research and development, immunotherapies, pharmaceutical productivity improvement and clinical trials.[1,3] Artificial Intelligence is also used in drug development.[4] Learn how to compute the QM/MM of an enzyme's active site.[5] Locate some lead-like library chemicals.[6] Only a few companies have agreed to participate in an AI-related study that could be employed in medicine discovery and creation. Euretos is employing massive omics-like datasets to investigate links between biological circuits and diseases.[7] Sparrho's goal is to help the technical community by extracting and curating the most relevant scientific research findings from a growing corpus of literature, employing both AI and human editors.[8] BioXcel is repurposing traditional medications using artificial intelligence.[9],[10] Creativity is used to identify and answer unmet medical needs.

The goal of this article is to look at recent advancements in Artificial Intelligence in medicine, as well as provide insight into the challenges and risks that health practitioners and institutions face when integrating augmented medicine into medical treatment and future medical leader education, as well as the most common use-cases where AI-powered therapeutic technologies are already being used in medical care.

ARTIFICIAL INTELLIGENCE APPROACHES

Artificial Intelligence (AI)

A higher level of education

A type of network is Artificial Neural Networks.

A well-known example of Artificial Intelligence is machine learning (AI). This method allows computers to reliably adapt and change their functions (e.g., making predictions).

AI is being employed in a wide range of disciplines. (Fig 1)

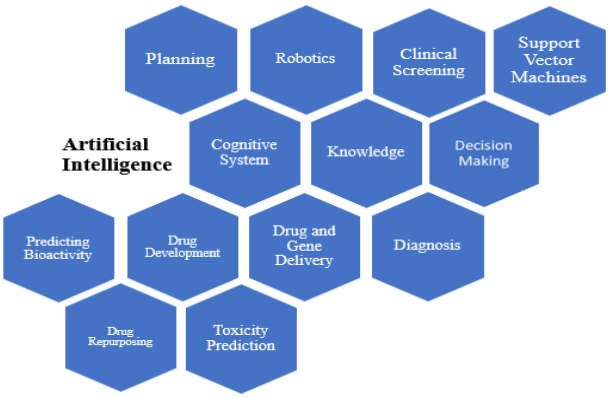

Figure 1: Artificial Intelligence is being used in a variety of fields.

Advancement of Artificial Intelligence (Fig 2)

I. Machine Learning

There are two types of machine learning algorithms.[11]

1) Observed learning

In supervised learning, the algorithm makes adjustments in order to respond effectively to a set of training cases. As a result, the anticipated output replies are known to be accurate, and feedback statistics are saved in the database for future training.[11] Regression analysis techniques include support vector machines, random forests, and Artificial Neural Networks.[11,12]

2) Unrestricted Learning is based on non-example-dependent feature extraction methods.[11] Other machine learning approaches, such as the probabilistic reasoning method, are also used in pharmaceutical sciences. To explain the logic and reasoning behind the assertions.[13] This method has the advantages of requiring no expert knowledge of the system, compensating for data noise, and providing easily interpretable projections.[14] This method can also be used to model nonlinear relationships. In pharmaceutical research, GA is frequently used as a feature selection method in quantitative QSAR studies.[15,16] Transfer learning is included in active machine learning. The technique of leveraging a previously trained model to construct a new, anticipated fit for the desired aim is known as transfer learning.[17] The database size of the initial formulation is a critical determinant of transfer learning performance.[18]

II. Artificial Neural Network

Artificial Neural Networks (ANN) are a sort of Artificial Neural Network that can be utilized in a variety of applications.

An Artificial Neural Network (ANN) is a model that simulates the brain's ability to learn by example. The interconnectedness of these neurons is made up of several synapses connecting one neuron to the next.[19] In a biological system, a neuron is made up of three parts: a cell membrane with a nucleus that regulates cellular activity, nerve cells that connect neurons and give signals to the cell, and axons, which look like one long thread carrying data to the next cell.[19] ANNs, like human neurons, are made up by clusters of neurons (PEs) connected by coefficients (weights).[19] The inputs, hidden, and SoftMax layers are the four fundamental structural systems of a traditional ANN. The system's input is the first layer of an input neuron, which corresponds to the synapses of a true neuron. The layers exist between the

source and destination nodes. Each buried layer[20] is densely packed with neurons. To put it another way, they're a network of interconnected advanced computer bits called 'perceptons,' which resemble biological neurons and respond to electrical impulses similarly to the brain.[21] ANNs are a sort of network that solves problems by converting discrete inputs into outputs using algorithms, either individually or in groups.[22] To construct supervised learning that can learn to solve an issue rapidly, repeated intake amounts of antecedent with known responses are used (targets). This is referred to as "learning" or "training." Receiving signals (inputs) from the input layer is the initial step in the learning process. In the hidden layer, these inputs are amplified and summed using network parameters. A transfer function is used to send the results to the output nodes. The activation functions accessible include logistic, tanh, identity, and exponential.[23] The transfer function is a commonly utilized activation function in medicine. In neural network learning, error back-propagation is an extensively used approach.[24] In addition to assessing complex data based on elongation and pattern recognition, ANNs are particularly good at simulating nonlinear interactions and collecting extremely precise predictions.[25,26] The disadvantages of utilizing ANNs include local minimum trapping, noise management, and overfitting/underfitting. The Time Invariant Noise Algorithm (TINA) is used to prevent local minima and control noise. Overfitting can be reduced with this method. Furthermore, stopping the technique at the right time can help prevent both overfitting and underfitting.[29]

III. Deep Learning

DL is both a Deep-Learning and a representational learning approach.[30] Recent breakthroughs in neural networks are included in the state-of-the-art of DL paradigms. The primary difference between ANNs and DLs is that DLs have many more hidden layers (always more than three) and each layer has many more nodes. DL employs a multi-level representation method to learn complex functions. The architecture of Deep Learning often necessitates a large amount of training data, which may limit its application. Deep learning uses CNNs, RNNs, and tightly integrated FFNs (Feed-Forward Networks) as neural network topologies.[31] In a number of pharmaceutical research domains, including as pharmaceutical formulation design[32], drug development[33], and medication retrofitting[34], DL has become vital and of exceptional quality.

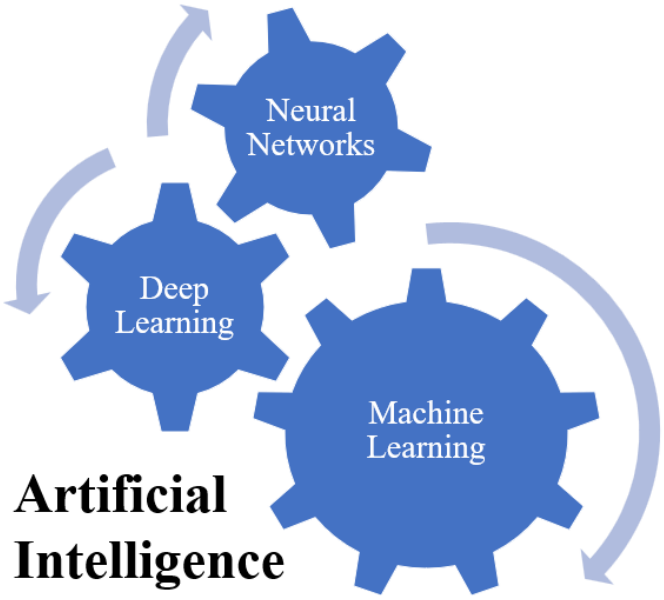

Figure 2: Advancement of Artificial Intelligence

➢ **Machine Learning Drug Prototyping and Revelation**

Due to the widespread use of HTS (High-Throughput Screening), CC (Combinatorial Chemistry), and computer-aided drug design in pharmaceutical sciences, drug discovery accounts for a significant number of algorithms (CAD).[35] One of the first ANN applications was in the QSAR research investigations.[36,37] The QSAR criterion connects a substance's physical and chemical properties with its biological and chemical activity.[38,39]

In Quantitative Structure Activity Relationship Structure QSAR research, chemical properties such as molecular weight, partition coefficient (logP), and hydrogen bonding capacity are commonly used. Because empirical QSAR research involves complicated and nonlinear systems, ANNs were one of the most accessible QSAR modelling methods. As seen by the rapid rise of QSAR research based on ANNs[40], the utility of neural networks in drug development has continued to grow as a result of their power grid and success.

➢ **IN PHARMACOLOGICAL SCIENCES, MACHINE LEARNING**

In recent years, machine learning has been used in a wide range of pharmaceutical applications, from drug discovery to the final stages of development. The following are the three main areas of pharmaceutics where ANNs and other machine learning technologies have been actively used. Drug design and development, preformulation, and formulation research are the three sorts of investigations.

➢ Artificial Intelligence and Drug Development (AI)

Developing novel medications that are effective is a difficult task. The situation is clarified by.[41] For drug target definition and validation, drug design, drug repurposing, R&D efficiency, biological data gathering and analysis, and refining the decision-making process to enrol patients in clinical trials, AI technologies have been used at many stages.[42,43] AI applications that reduce inefficiencies, uncertainty, bias, and human participation could help traditional drug development procedures.[44] AI is also used in drug development to predict drug-like chemical synthetic pathways[45], pharmacological properties[46], protein determinants and functions[47], drug synergy and drug–target interactions[48], and medicine repurposing.[49]

New pathways and targets found by omics research include therapeutic targets, customised treatment based on omics indicators, and exposing the links between drugs and disorders.[50,51] DL has a history of recognizing novel drug concepts and appropriately appraising their advantages as well as any potential negative effects.[52] New research could use AI to aid in the identification of new therapy targets, rational prescription design, and pharmaceutical repurposing.[55,56] Previous drug development challenges, such as large dataset analysis and time-consuming compound screening while minimizing standard error, necessitated massive amounts of R&D money and effort, totalling around US$2.5 billion and spanning more than a decade[53], are now possible to overcome with AI technologies.[54]

➢ Artificial Intelligence in Pharmaceutical Manufacturing

I. Tablets with a controlled release

Hussain and his colleagues at the University of Cincinnati were the first to employ neural networks to simulate pharmaceutical formulations. They patterned the in vitro release properties of a number of medicines implanted in matrices made from various hydrophilic polymers in a series of investigations.[57,58] In every situation, neural networks with a single convolutional layer performed well in forecasting drug release. Overall, the findings corroborated statistical analyses.[57] On the other hand, predictions made outside of the limits of the input data performed badly.[58] Even though evolutionary methods were not utilized to update the formulations, the researchers were inspired to look into neural network-based computer-aided formulation design.[58]

II. Immediate-release tablets

Two tests were conducted in this location three years ago. Turkoglu collaborated on a study[59] with colleagues from the University of Marmara in Turkey and the University of Cincinnati to forecast hydrochlorothiazide tablet formulations using neural networks and statistics. To increase tablet strength or find the best lubricant, the networks were utilized to create three-dimensional plots of massing time, compression pressure, and crushing strength, as well as drug release, massing time, and compression pressure. Even though patterns were found, no ideal formulations were given. The patterns were created using statistical methods.

In a more in-depth research of neural networks in this domain, Kesavan and Peck of Procter & Gamble Pharmaceuticals (Norwich, NY, USA) and Purdue University (West Lafayette, IN, USA) duplicated the manufacture of anhydrous caffeine tablets. Two networks were created from 32 tests, one with five inputs [diluent type, diluent level, binder level, granulation machinery used, and binder addition (wet or dry)] and the other with nine inputs [diluent type, diluent level, binder level, granulation machinery used, and binder addition (wet or dry)]. In forecasting findings, both models were more accurate than hastily generated models with four outputs (tablet strength, friability, thickness, and disintegration time). The AI Ware CAD/Chem application[60] was used to re-analyse the same data.

Comparable neural network models were created and optimized using genetic algorithms. The optimum formulation was shown to be dependent on both the chemical concentrations used in the formulation and the relative importance of the output qualities. Only by sacrificing disintegration time can high tablet strength and low friability be achieved. Lactose was utilized as a diluent in all cases, and the granulating analytical technique of choice was fluidized bed granulating.[61]

- **Artificial Intelligence Drug Screening**

A medication's research and development can take a decade and cost an average of $2.8 billion. Despite this, authorities reject nine out of ten medication candidates that fail Phase II clinical trials.[62,63] Nearest-neighbour filters (RF), ensemble learning machines (SVMs), and Deep Neural Networks (DNNs) are utilized to predict in vivo activity and toxicity in the case of VS. In areas like immuno-oncology and cardiovascular disease, pharmaceutical corporations like Bayer, Roche, and Pfizer have partnered with IT businesses to construct drug development platforms.[62]

- **Creating Drug Molecules using Artificial Intelligence**

The target protein's estimated structure in order to accomplish successful therapy, it is necessary to designate the proper target while generating therapeutic molecules.[63] Several proteins have been uncovered as the illness progresses, some of which have been found to be overexpressed in some patients.[64] As a result, while creating a disease-targeting medicinal chemical, it's crucial to forecast the structure of the target protein. AI can help structure-based regenerative medicine by predicting the impact of a drug on the aim as well as its restrictions prior to its synthesis or manufacture by anticipating the 3D protein structure.[65] AI can aid structure-based regenerative medicine by predicting 3D protein structure since the design is in agreement with the chemical environment of the target protein location.[66]

- **For quality assurance and control, artificial intelligence (AI) is being applied**

To obtain the necessary output from raw resources, a variety of attributes must be balanced.[67] For product quality control testing and batch-to-batch consistency, manual intervention is essential. While this isn't always the best solution, it does highlight the urgent need for AI adoption.[68] To better comprehend the critical actions and exact criteria that manage a pharmaceutical product's ultimate quality, the FDA suggested a 'Quality by Design' method.[69] Using a combination of human and AI efforts, early discoveries from production batches were reviewed, and feature selection algorithms were constructed. ANN was used to investigate the solubility and dissolving rate of theophylline pellets[70], with an error rate of less than 8%.

AI can also be used to control in-line manufacturing activities to achieve the appropriate product grade. An Artificial Neural Network (ANN) that combines auto evolution, multi-objective, and training algorithm methodologies is used to monitor the freeze-drying process. This can be utilized to predict temperature and desiccated-cake thickness at a later time point (t + t) for a given set of operational parameters, making quality control of the finished version easier.[71] Product reliability can be ensured by combining a complex, intelligent technique with an automated data input platform, such as an Electronic Lab Notebook.[72] The Total Quality Management expert system may employ data mining and other knowledge discovery approaches to aid in making challenging judgments and inventing new technologies for intelligent quality management.[73]

➢ Clinical Trials with AI in the Works

Clinical trials are used to test a pharmaceutical medication's safety and efficacy in people who have a specific ailment. They necessitate a large financial investment and require 6–7 years to finish. Despite this, just one out of every ten substances tested in these trials gets approved, resulting in a significant loss for the industry.[74] These failures can be caused by a lack of patient selection, a lack of technology expectations, or a damaged infrastructure. AI could be utilized to help resolve these challenges because digital health data is publicly available.[75] A clinical trial spends one-third of its time seeking volunteers. Enrolling competent patients can help a clinical study succeed, despite the fact that it has an 86 percent failure rate.[76] AI can assist in the selection of only a certain sick population for enrolment in Phase II and III clinical trials by using patient-specific genome–exposome profile analysis, allowing for the early identification of promising therapeutic targets in the patients chosen.[77] Using other AI components to uncover therapeutic targets ahead to the start of clinical trials, such as predictive ML and other reasoning approaches, aids in the early prediction of lead medications that will pass clinical trials while considering the patient population.[78] Dropouts from clinical trials account for 30% of study failures, requiring further recruiting and losing time and money. This can be avoided by monitoring and aiding participants in adhering to the clinical study procedure on a regular basis.[79]

➢ Artificial Intelligence for Market Positioning

Many business strategies for firms attempting to build their own distinct brand include a positioning plan. It comprises establishing a product's identity in the marketplace in order to entice people to buy it.[80,81] This method was used to promote Viagra, a game-changing drug used to treat erectile dysfunction in men as well as other quality-of-life issues.[82] Through the use of technology and e-commerce as a platform, businesses may now build natural brand awareness in the public realm. According to the Internet Advertising Bureau, organizations use search engines as one of the technology platforms to get a competitive advantage in digital marketing and aid in product placement. Companies are constantly attempting to outrank their competitors websites in order to gain visibility for their brand.[83] To improve market knowledge, statistical analysis methodologies and particle swarm optimization algorithms, for example, can be employed in conjunction with NNs (Developed by Eberhart and Kennedy in 1995). They can help build a product marketing plan that is based on realistic client demand projections.[84]

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