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A REVIEW OF ARTIFICIAL INTELLIGENCE IN PHARMACEUTICAL PRODUCT DEVELOPMENT.

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ABSTRACT

Artificial intelligence (AI) has developed into a useful technology that makes use of human expertise and provides speedier solutions for challenging issues. Significant advancements in AI and machine learning technology have the potential to revolutionize the drug discovery process. the creation and assessment of drug dose formulations. By leveraging a plethora of biological data, including proteomics and genomes, artificial intelligence systems enable scientists to forecast the relationships between putative therapeutic candidates and targets linked to disease. As a result, drug discovery can be approached with greater effectiveness and attention, increasing the likelihood of a successful medication authorization. The possible ways in which artificial intelligence (AI) could improve the efficiency of the process of developing new pharmaceutical products and the collaboration between the main players in the pharmaceutical industry and AI-powered drug research companies. This evaluation focuses on the advantages and disadvantages of the various AI-based pharmaceutical technology techniques. Ongoing research and investment in artificial intelligence by the pharmaceutical business, however, offers exciting prospects for methods of product creation.

INTRODUCTION

The definition of artificial intelligence is an expansive subject matter. This is one:

The study of the algorithms that support perception, cognition, and action is known as artificial intelligence. By this definition, artificial intelligence differs from conventional computer science and psychology in that it places more of an emphasis on computation and less on perception, reasoning, and action.

Artificial intelligence can be understood as a synthesis of science and engineering when taking goals into account. The engineering goal of artificial intelligence is to be used as a collection of concepts for information expression, knowledge application, and system construction.

The scientific goal of artificial intelligence is to comprehend the theories pertaining to knowledge expression, knowledge utilization, and the construction of systems that collectively account for various forms of intelligence.

One important industry segment that is necessary to save lives is the pharmaceutical industry. It functions through ongoing innovation and the adoption of cutting-edge technologies to address global healthcare concerns and respond to medical emergencies, such as the most recent pandemic. The pharmaceutical industry can benefit greatly from artificial intelligence (AI) in a number of ways, including process design and control optimization, intelligent maintenance and monitoring, and trend analysis to support continuous improvement. To get the desired results, artificial intelligence (AI) in pharmaceutical product development can be coupled with other state-of-the-art manufacturing methods. [1-3]

Fig 1: AI in Pharmaceutical Products Development

HISTORICAL BACKGROUND

In 1950, Alan Turing presented the concept of computer simulation of intelligent behavior and critical thought. He provided a simple test in his book "Computers and Intelligence" to determine whether computers are capable of human intellect (after termed the "Turing test"). Six years later, John McCarthy stated that artificial intelligence (AI) is the science and engineering of building intelligent machines. Artificial intelligence (AI) has evolved over several decades from a basic collection of "if-then rules" to more sophisticated algorithms that function similarly to the human brain.

Among them are machine learning, deep learning, and computer vision. Machine learning, or ML, is the application of distinctive features to discover patterns that can be used to analyze a particular situation. The computer will then have the ability to "learn" from that information and apply it to similar situations in the future. This prediction tool can be used dynamically to assist clinicians in making judgments that would better adapt treatment for individual patients, as opposed to relying on a fixed technique. Deep learning (DL) has gained popularity as machine learning (ML) has progressed. DL consists of methods that construct an artificial neural network (ANN) with self-learning and decision-making capabilities, akin to those of the human brain. [4, 5]

THE BASIC CONCEPT OF AI IN PHARMACEUTICS

AI advancements can be divided into two categories. The first group includes software, technology techniques, and expert systems that simulate human experience and make decisions based on predefined criteria. Artificial neural network devices, or ANNs, are a subset of the second class of devices that mimic brain activity. The ability of artificial neural networks to generalize is one of its biggest advantages. Because of these qualities, they are highly suited to handle issues related to formulation optimization that arise during the development of pharmaceutical products.

The ability of a robot or digital computer under computer control to execute tasks typically carried out by intelligent individuals is known as artificial intelligence (AI). The term is commonly employed in the endeavor to develop artificial intelligence (AI) systems that exhibit cognitive abilities like to those of humans, including reasoning, discovering meaning, generalization, and experience-based learning. It has been known since the 1940s, when the first digital computers were developed, that computers are capable of learning to do incredibly complex jobs. These days, the pharmaceutical industry only approves medications following a drawn-out and costly drug research procedure. The majority of drugs cost billions of dollars and take ten years or more to break into the pharmaceutical market. This results in longer and more expensive drug development times.

In order to overcome these drawbacks, the artificial intelligence (AI) concept appears more promising and ought to result in successful pharmaceutical development programs. Prosthetics, advanced robots, and pharmaceuticals are among the emerging technologies that are incorporating artificial intelligence. Additionally, AI can be used to identify possible therapeutic targets, suggest chemically modified compounds

from data libraries, and even repurpose already-approved medications. The artificial intelligence method being employed leverages machine learning or any of its subsets, such as deep learning and natural language processing. It is possible to learn both supervised and unsupervisedly, and the type of method that is employed is also crucial. supervised learning is a machine learning method that uses known inputs (features) and outputs (labels or targets), as opposed to unsupervised learning, which operates with uncertain outcomes. Several inputs or attributes, such labels or targets, are employed in the supervised technique to predict the output. Unsupervised classification, on the other hand, aims to create feature-homogeneous clusters. [6-9]

Table 1: Commonly Used Learning sModel

AI/Machine Learning Models	Description/Usage
Generative Adversarial Networks (GANs)	GANs are frequently utilized in the development of pharmaceutical products in order to generate distinctive chemical compounds and optimize their properties. GANs are made up of a generator network that creates new molecules and a discriminator network that evaluates the quality of freshly formed ones in order to produce structurally varied and functionally optimal therapeutic candidates.
Recurrent Neural Networks (RNNs)	RNNs are widely employed in drug development for sequence-based tasks such as protein structure prediction, peptide sequence design, and genomic data analysis. They understand sequential interdependence and can create new sequences based on patterns they have learned.
Convolutional Neural Networks (CNNs)	CNNs perform well in image-based applications such as assessing chemical structures and identifying potential therapeutic targets. By removing relevant details from molecular images, they can aid in target identification and medication creation.
Long Short-Term Memory Networks (LSTMs)	One application of LSTMs, a type of RNN, is temporal relationship modeling and forecasting. They have been used in pharmacokinetics and pharmacodynamics research to predict medication concentration-time patterns and evaluate treatment efficacy.
Transformer Model	Pharmaceutical companies have employed transformer models to address issues with natural language processing. Bidirectional Encoder Representations from Transformers, or BERT, is one well-known model. Researchers can extract useful data from databases containing patents, clinical trial data, and scholarly articles to aid in the development of novel medications.
Reinforcement Learning (RL)	RL methods have been applied to generate effective medicine dosing algorithms and personalized treatment regimens. Reinforcement learning (RL) systems learn from interactions with the environment to produce consecutive judgments that aid in dose optimization and improve patient outcomes.
Bayesian Models	Bayesian models, such as Bayesian networks and Gaussian processes, are used in drug development to quantify uncertainty and make decisions. They make it easier for researchers to create probabilistic hypotheses, assess risks, and optimize experimental designs.
Deep Q-Networks (DQNs)	Deep question networks (DQNs), which combine deep learning and reinforcement learning, have been used to optimize drug development procedures by predicting compound activity and recommending high-potential candidates for further testing.
Autoencoders	Autoencoders are unsupervised learning models used in drug development for dimensionality reduction and feature extraction. They can aid in compound screening and virtual screening by capturing important molecular characteristics.

Graph Neural Networks (GNNs)	GNNs are appropriate for drug discovery activities involving molecular structures because of their ability to analyze graph-structured data. They can help with de novo drug discovery, virtual screening, and property prediction. They can also model molecular graphs.

AI APPLICATION IN DOSAGE FORM DESIGNS

The effects of medication administration are examined in a range of bodily compartments in humans. Further compartment simplification is based on the biological membranes. Physical-chemical barriers can be implemented in a way that complements the body's natural medication delivery system and are necessary for biological compartments. For efficient drug delivery system monitoring, one of the most crucial parameters is the rate of penetration based on the administration route. For an oral drug to reach the stomach environment, it must pierce the intestinal or gastric epithelium. This phase is necessary for the drug's continuous bloodstream dispersion. During the distribution process, the medication is administered to the target place, which could be tissue or any of the several cellular components. In order to penetrate the body, drugs might also target intracellular molecules. Most drug penetration is aided by biological barriers, either active or passive. Passive diffusion is governed by the molecular properties of the medication. The in-silico models are used to predict drug distribution by computing analysis; nevertheless, the results differ slightly from the actual drug distribution study. A medication's availability in biological environments and its interactions with biological components have a significant impact on how the medication functions in the body. This process is governed by the drug's molecular characteristics. For many physiologically active chemicals and small molecules, passive permeation is ineffective, requiring the adoption of a specific drug delivery technique. The process of active penetration is driven by membrane transport and is reliant on complex biological interactions. This complex process must be studied by means of computer and systematic modeling approaches with a variety of accurate components. This updated computer model is used to study the pharmacokinetic properties of the drug delivery system. One of the primary shortcomings in the pharmacy sector's research and development is the predictability of preclinical models. Complex in silico models are not an exception to the selectivity assumption, which is based on the parameters that are selected. [10-12]

Fig 2: AI Application in Dosage Form Designs

One benefit of AI is that it collects information from multiple sources and recommends the best medicine delivery method to use in order to get the intended results. To find the best active drug to treat a patient's illness or suit their demands, a complex data analysis procedure may involve assessing molecular information, patient data, and pharmacokinetic data. Using the passive form of artificial intelligence, the properties of a chemical entity are identified by comparing them with those of known molecules. Treatment effectiveness is determined by how precisely drug delivery systems are selected, which is a function of artificial intelligence. [13-14]

AI FOR DRUG DELIVERY

Computational pharmaceutics, which employs multiscale modeling tools to enhance medicine delivery systems, is a product of the pharmaceutics discipline. This is the outcome of pharmaceutics' use of big data and AI integration. Computational pharmaceutics uses AI algorithms and machine learning techniques to analyze large datasets and predict drug behavior. By simulating the medication formulation and delivery processes, researchers can evaluate various scenarios and optimize drug delivery systems without the need for drawn-out trial-and-error experiments. This reduces costs, expedites the time needed to investigate novel medications, and increases productivity. In computational pharmaceutics, drug delivery systems are modeled at multiple scales, ranging from molecular interactions to macroscopic behavior. Artificial intelligence systems may analyze complex relationships between formulation components, physiological data, and pharmacological properties to predict drug activity at all scales. This facilitates the development of efficient drug delivery devices and allows for a larger understanding of drug delivery mechanisms. It helps predict the stability, physicochemical properties, and in vitro drug release profile of the treatment. The same method is applied for improved assessment of in vivo pharmacokinetic parameters and drug distribution in addition to in vivo-in vitro correlation studies. By using the right mix of artificial intelligence approaches, researchers can identify potential risks and challenges associated with medication delivery systems early in the development phase. [15-17]

This enables proactive changes and adjustments to minimize risks and enhance the efficacy of medication. Computer modeling and artificial intelligence (AI) reduce the possibility of unexpected outcomes by eliminating the need for expensive and time-consuming trial-and-error experiments. [18]

AI FOR ORAL SOLID DOSAGE FORM DEVELOPMENT

Modern technology and software are used by AI to create human-like abilities. This kind of innovation has proven useful in the last few years across a wide range of businesses, including the pharmaceutical industry, especially during the product development phase. The time, money, and resources required for production and the effective supply chain delivery of goods to final consumers can be decreased by utilizing these technological improvements. It also provides a more thorough framework for understanding how manufacturing and product development are impacted by process characteristics. Run Han et al. looked at predicting the stability of solid dispersion over a six-month period using machine learning approaches. Hanlu Gao et al. looked at the application of machine leaching in solid dispersion dissolving experiments. They used a random forest technique to generate a classification model that helps further distinguish between the spring and parachute types of dissolution patterns. Furthermore, with a sensitivity and accuracy of 86% and 85%, respectively, it supported supersaturation. The time-dependent release of the drug was predicted using the regression model produced by the random forest technique. [19-21]

In the pharmaceutical sector, where solid dosage forms are the standard, tablets are one of the most commonly utilized dose forms. There are many ingredients in the preparation of tablets, depending on the kind. AI can help with both the investigation of the necessary characteristics needed for the formulation and the pursuit of its ideal form. AI is also expected to manage responsibilities through the use of automated technologies and algorithms. The use of AI has made it difficult for regulatory agencies to update existing guidelines about current good manufacturing practice (cGMP). Neural networks, fuzzy logic, genetic algorithms, and other technologies are all included in the category of artificial intelligence (AI). Solid dosage forms can be created with these technologies, which also help to better comprehend inputs and outputs for operations and processing. Artificial neural networks (ANNs) are used to enhance prediction skills for solid dosage forms, whereas genetic algorithms are utilized to forecast the results of employing input parameters. [22-25]

Table 2: List of commonly explored AI models in pharmaceutical product development.

AI/Machine Learning Models	Description/Usage
Genetic Algorithms	Genetic algorithms are optimization techniques inspired by genetics and natural selection. They can be utilized to enhance drug release patterns, formulation compositions, and process parameters to acquire the necessary dosage form qualities.
Artificial Neural Networks (ANNs)	Artificial neural networks have been used to model and optimize the kinetics of drug release from different dose forms. They can assist in identifying the most effective formulations and project the release profile of active pharmaceutical ingredients (APIs) in various scenarios.
Particle Swarm Optimization (PSO)	PSO is a population-based optimization technique that can be used for dosage form optimization. It has been used to optimize the dissolving profiles, particle size distribution, and other formulation factors.
Artificial Intelligence-based Expert Systems	Expert systems use artificial intelligence (AI) techniques like fuzzy logic and rule-based systems to simulate the decision-making process of human experts. They can be applied to optimize dose forms by considering different aspects of the process and formulation.
Computational Fluid Dynamics (CFD)	CFD simulations enable the optimization of fluid flow and mixing throughout dosage form production processes, including granulation, coating, and drying. They aid in the development of dependable, efficient procedures.
Response Surface Methodology (RSM)	RSM is a statistical technique that aids in the optimization of dosage form formulations by modeling and analyzing the relationship between a number of variables and how it impacts formulation responses. It makes understanding and fine-tuning formulation parameters easier.
Multivariate Analysis Techniques	Multivariate analysis methods such as principal component analysis (PCA) and partial least squares (PLS) have been used in dosage form optimization. They facilitate the identification of critical formulation parameters, formulation performance optimization, and dimensionality reduction.

Tablets are a well-liked solid dosage that account for a sizeable chunk of the drug delivery market. During the creation process, active medicinal compounds and additives are used to achieve the required form and dimensions. After that, these components are moulded or crushed. A range of excipients are added to tablets in order to regulate the desired product outcome, such as medication release, dissolving, and tablet disintegration. These components have been specified by the formulator to meet the specific needs of the target patient population. Two examples of excipients that are essential for optimizing the manufacturing process are lubricants and glidants. In the context of systemic drug delivery, AI can also be utilized to predict drug release. Additionally, it is employed to investigate the effects of crucial processing factors that are necessary for the manufacturing of tablets in order to ensure consistent quality control procedures. Some artificial intelligence programs have been used to identify weaknesses in tablets. [26-28]

PREDICTION OF DUG RELEASE THROUGH FORMULATIONS

It is undoubtedly possible to achieve stable quality control with medicine release prediction. Drug release studies are conducted using in vivo and in vitro techniques, which are considered core technologies that are regularly evaluated or tested during product development. The drug is released from oral solid dosage forms upon the combination of processing parameters and necessary material properties. Some of the common elements influencing drug release are the geometric features of the tablets, the qualities of the drug loading, and the pressure employed to set the tablet's hardness. Compaction parameters are also important. A variety of analytical methods have been employed, including spectrophotometric procedures, and drug release studies are usually required for a thorough analysis. [29, 30]

ORAL FORMULATIONS – IMMEDIATE RELEASE

Turkoglu et al. performed the first study in this field by modeling a direct compression tablet formulation containing hydrochlorothiazide in order to maximize tablet strength and select the best lubricant. In a study, Kesavan and Peck created a caffeine tablet and investigated the relationship between granule and tablet properties (hardness, friability, and disintegration time) and formulation variables (diluent type and concentration, binder concentration) and processing variables (granulator type and method of adding binder). Neural networks surpassed conventional statistical methods, as these two research showed. Following that, a new analysis of the Kesavan and Peck data was conducted using a neural network and genetic algorithm combination. This illustrated that the optimal formulation is contingent upon the constraints placed on the component levels and processing variables, in addition to the proportionate weight assigned to the output attributes. Many ideal formulations may be produced, depending on the "trade-offs" that may be tolerated for different aspects of product performance. The same collection of data has been examined using neurofuzzy computing. Automatic generation produced useful guidelines that highlighted the essential components of each characteristic and their interdependencies. The parameters controlling disintegration time included the diluent itself, the concentration of the binder, the addition of the binder (wet or dry), and the granulation process. The rules influencing friability and tablet hardness are, as one might expect, the reverse of each other. [31-32]

In addition to immediate release tablet formulations, neural networks have been used to formulate rapidly disintegrating or dissolving tablets, immediate release capsules, and a novel oral microemulsion formulation of isoniazid and rifampin for the treatment of children during the continuation phase of tuberculosis. Neural networks and neurofuzzy have recently been used to reliably forecast ketoprofen solid dispersion compositions. The investigation's scope has been expanded by the addition of a microemulsion formulation. [33]

CONTROLLED RELEASE ORAL FORMULATIONS

Chen et al. used artificial neural networks (ANNs) and pharmacokinetic simulations to design controlled-release formulations. Seven formulation variables and three extra tablet variables (moisture, particle size, and hardness) for 22 tablet formulations of a model medication were the inputs for the ANN model. The cumulative percentage of medicine released in vitro at ten different sampling times was the outcome. The input and output data sets were used to develop and train the ANN model using CAD/Chem software. Using the trained ANN model, two desired in vitro release profiles and two wanted in vitro dissolve-time profiles were used to determine the optimal formulation compositions. The authors state that the medication's dissolution is the rate-limiting phase of its in vivo absorption and that there is a linear correlation between the percentage of the drug absorbed in vivo and its in vitro dissolution. Three of the four projected formulas showed very good agreement between the expected ANN and the observed in vitro release profiles based on similarity factor (f2) and difference factor (f1). [34, 35]

The film that is applied to coated tablets often regulates the drug's release, while occasionally the tablet core's composition may also have an impact. In pelleted or multi-particulate formulations, the drug release mechanism can be regulated by films or a rate-controlling matrix. The pellets are made by either spheronization and extrusion or by stacking over sugar cores. There are situations where the pellets may be tableted. In others, they are encased in stiff gelatin capsules. Peh et al. successfully mimicked the release of theophylline from a matrix controlled release pellet formulation created by extrusion and spheronization using recurrent neural networks and multi-layer perceptrons. [36]

Recently, a bimodal drug delivery system made up of pellets coated with chitosan and pectin was mimicked using neural networks trained using five distinct training techniques. The networks that were trained with backpropagation methods based on gradient descent outperformed the others. Pillay and Danckwerts estimated the textural properties of a novel pellet formulation that was able to significantly gel and swell in biological fluids using both statistics and neural networks. The formulation's inventor gave it the moniker "gelisphere." [37]

APPLICATION OF AI FOR 3D-PRINTED DOSAGE FORMS

With its application in 3D-printed dosage forms, artificial intelligence (AI) has revolutionized the pharmaceutical manufacturing sector in two ways: through personalized medication and enhanced drug delivery systems. By optimizing the design and formulation of 3D-printed dosage forms based on patient-specific factors like age, weight, and medical history, customized pharmacological therapy can be realized. Through the use of machine learning and computational modeling, AI is able to analyze enormous datasets and simulate the behavior of 3D-printed dosage forms. This makes it possible to quickly prototype and optimize dosage levels, geometries, and drug release patterns. AI is also useful for optimizing printing parameters, keeping an eye on quality, and foreseeing and resolving any production problems. By learning from real-time data, AI-driven feedback systems can also be used to continuously improve 3D printing processes by increasing accuracy, reproducibility, and scalability. All things considered, 3D-printed dose forms with AI hold great potential for improving patient outcomes and personalized treatment. [38, 39]

The 3D-printed tablets are made using the fused-filament method of fabrication, pressure microsyringe, laser sintering, and jetting of the binder. Some of the crucial processing parameters influencing the 3D-printed tablets are the temperature of the nozzle and platform as well as the printing speed. Obeid et al. used an ANN model to demonstrate how the processing parameters affected a diazepam-containing 3D-printed tablet and the subsequent drug release investigation. They looked into the infill pattern, infill density, and other input factors to successfully dissolve medications into 3D-printed tablets. Self-organizing maps were employed to evaluate the connections among the different variables. In later modeling studies, the volume ratio and infill density throughout the surface area remained the primary factors influencing the same. A higher dissolution was attained following extensive testing and ANN modeling in conjunction with validation. [40]

APPLICATION OF AI FOR THE DETECTION OF TABLET DEFECTS

Pharmaceutical manufacturing quality control processes have undergone a radical transformation as a result of the application of AI to detect tablet defects. Artificial intelligence (AI) algorithms and computer vision techniques are used to evaluate tablet images, enabling the automatic and efficient detection of defects including as chips, fractures, discoloration, and changes in size and shape. AI models are trained on large datasets of tagged photographs, enabling the system to learn how to accurately classify and identify different types of defects with high recall and precision. Conventional methods such as X-ray computed tomography have been used to investigate the internal structure of tablets; however, these methods are still time-consuming and impede the demand for rapid tablet production. To detect tablet issues, X-ray tomography and deep learning are integrated. Ma and colleagues examined the use of neural networks in tablet fault detection using X-ray tomography image processing. [41, 42]

These scientists have produced multiple batches of tablets using mannitol and excipients like microcrystalline cellulose. The so-called image augmentation approach was applied to the resulting batches for analysis. In the same study, three other models were employed, including UNetAs, which can be utilized to differentiate between the features of tablets and bottles. AI integration for tablet defect detection ultimately results in higher-quality products, increased productivity, and assurances regarding the efficacy and security of medications. [43]

CONTRIBUTION OF AI TO DISSOLUTION RATE PREDICTIONS

The pace at which a medicine dissolves in a biological fluid is known as its dissolution rate, and it plays a major role in determining both its bioavailability and therapeutic effectiveness. By forecasting disintegration rates, artificial intelligence has greatly enhanced dosage forms and medication formulations. By examining vast amounts of experimental data, AI models are able to identify the crucial physicochemical properties and molecular components that influence the dissolving process. These models employ machine learning algorithms to find complex relationships and patterns between the properties of the medicine and its rate of breakdown, enabling them to produce accurate forecasts. By providing insights into the dissolving behavior of different drug formulations, artificial intelligence (AI) helps with the creation of more effective drug delivery systems as well as the selection of the optimum formulation strategies for increased drug solubility and absorption. Thanks to AI-powered dissolving rate prediction, pharmaceutical professionals now have practical tools to expedite medicine development, improve formulation procedures, and ultimately improve patient outcomes.

Several studies have looked at how commonly prescribed drugs dissolve, and their findings indicate that certain drugs dissolve more quickly than others and that they tend to become supersaturated.

Amorphous drug recrystallization and precipitation are two further crucial components of this procedure. Multiple research have shown that the addition of an excipient does not induce solid dispersions to precipitate. [44]

AI APPLICATION FOR PARENTERAL, TRANSDERMAL AND MUCOSAL ROUTE PRODUCTS

Biologics and injectables are two examples of complicated formulations that can be designed and produced using AI. AI programs that forecast intricate physicochemical characteristics of pharmaceutical formulations may prove beneficial for the creation of new formulations. AI models analyze manufacturing processes, excipients, and formulation ingredients to enhance stability, pH, solubility, and viscosity. This helps create stable parenteral formulations. AI can optimize the production of parenteral products in terms of quality, efficiency, and variability. Large datasets from analytical testing, including spectroscopy, chromatography, and particle size measurement, may include variations and trends in product quality that AI systems can identify. This helps detect and resolve quality concerns early on, ensuring high-quality products. AI models can forecast contamination, stability, and regulatory deviations using process variables and historical data. Artificial intelligence (AI)-based monitoring systems have the potential to rapidly evaluate crucial process parameters in parenteral product manufacture. Through the amalgamation of data from sensors, instruments, and process controls, artificial intelligence systems may promptly identify anomalies, predict deviations, and initiate suitable measures. This lowers noncompliance while maintaining the caliber of the final output. AI simplifies difficult equipment maintenance procedures used in the production of oral products. Product uniformity, batch failure rates, and factory productivity all increase as a result. Artificial intelligence (AI) models use sensor data, equipment performance history, and maintenance records to anticipate equipment failure or deterioration and schedule preventive maintenance. This minimizes maintenance, boosts productivity, and keeps downtime unnecessary. AI can help with parenteral and sophisticated biological product regulation compliance. Artificial intelligence (AI) algorithms can evaluate compliance, spot any noncompliance problems, and provide recommendations for process improvement by looking at process data and product features. Both GMP compliance and regulatory compliance are supported by this.

Bannigan et al. emphasize the availability and promise of cutting-edge machine learning (ML) technology in the disciplines of materials science and pharmaceuticals. They demonstrate how accurately predicting the in vitro release of pharmaceuticals from long-acting injectables (LAIs) using machine learning (ML) could accelerate the development of novel drug delivery methods. The research emphasizes how interpretable machine learning models are and how they might provide insight into the process of making decisions. Neural network models performed poorly due to the small dataset, however tree-based models such as LGBM demonstrated potential in reducing the cost and time required to develop LAI formulations. The paper presents a proof-of-concept for ML in drug formulation with the goal of promoting future, more advanced, and specialized ML techniques. [45, 46]

CHALLENGES THAT PHARMA COMPANY'S FACE WHEN ATTEMPTING TO ADOPT AI INCLUDES

Artificial intelligence (AI) is still considered a "black box" by many pharmaceutical businesses due to its novelty and esoteric nature.

There is insufficient IT infrastructure because the majority of existing IT programs and systems were not created or developed with artificial intelligence in mind. The situation is exacerbated by the fact that pharmaceutical companies must upgrade their IT infrastructure at a significant financial cost.

Since most pharmaceutical data is in free text format, companies must go above and above to ensure that it is gathered and arranged for ease of analysis. Despite these disadvantages, it is indisputable that AI is revolutionizing the biotech and pharmaceutical industries. [47]

CONCLUSION

AI has shown to be beneficial in a wide range of product development domains. AI can help scientists with the planning, design, quality assurance, maintenance, and administration of pharmaceutical product development and distribution. AI is changing pharmaceutical delivery technology by enabling targeted, tailored, and adaptive treatments. By leveraging AI's advantages in data analysis, pattern recognition, and

optimization, pharmaceutical researchers and medical professionals can enhance patient outcomes, decrease side effects, and boost therapeutic efficacy. All things considered, the pharmaceutical industry has a great deal of potential to transform, advance from era 4.0 to era 5.0, and expedite the discovery of new medications by implementing AI technologies.

REFERENCE

1. Winston PH. Artificial Intelligence. 3rd ed. California: Addison Wesley; 1992.
2. G Terrelle E. We Cannot Win the Access to Medicines Struggle Using the Same Thinking That Causes the Chronic Access Crisis. Health Hum. Rights.2021; 23: 119–27.
3. Krikorian 1. Ramesh AN, Kambhampati C, Monson JR, et al. Artificial intelligence in medicine. Ann R Coll Surg Engl 2004; 86: 334-338.
4. Amisha, Malik P, Pathania M, et al. Overview of artificial intelligence in medicine. J Family Med Prim Care 2019; 8: 2328-2331.
5. Scannell J.W.; Blanckley A.; Boldon H.; Warrington B. Diagnosing the Decline in Pharmaceutical R&D Efficiency. Nat. Rev. Drug Discov. 2012; 11: 191–200.
6. Sharma R.; Shishodia A.; Gunasekaran A.; Min H.; Munim Z.H. The Role of Artificial Intelligence in Supply Chain Management: Mapping the Territory. Int. J. Prod. Res. 2022; 60: 7527–7550.
7. Sarpatwari A.; Barenie R.; Curfman G.; Darrow J.J.; Kesselheim A.S. The US Biosimilar Market: Stunted Growth and Possible Reforms. Clin. Pharmacol. Ther. 2019; 105: 92–100.
8. Sarker I.H. Machine Learning: Algorithms, Real-World Applications and Research Directions. SN Comput. Sci. 2021; 2: 160. [CrossRef]
9. Sarker, I.H. AI-Based Modeling: Techniques, Applications and Research Issues Towards Automation, Intelligent and Smart Systems. SN Comput. Sci. 2022; 3: 158. [CrossRef]
10. Dara S.; Dhamercherla S.; Jadav S.S.; Babu C.M.; Ahsan, M.J. Machine Learning in Drug Discovery: A Review. Artif. Intell. Rev. 2022; 55: 1947–1999.
11. Chavda, V.P.; Sorathiya, A.; Valu, D.; Marwadi, S. Role of Data Mining in Bioinformatics. In Computation in BioInformatics: Multidisciplinary Applications; John Wiley & Sons: Hoboken, NJ, USA, 2021; pp. 69–84. [CrossRef]
12. Parikh, S.; Patel, R.; Khunt D.; Chavda, V.P.; Vora, L. Data Analytics and Data Visualization for the Pharmaceutical Industry. In Bioinformatics Tools for Pharmaceutical Drug Product Development; John Wiley & Sons, Ltd.: Hoboken, NJ, USA, 2023; pp. 55–76. ISBN 978-1-119-86572-8.
13. Sousa T.; Correia J.; Pereira V.; Rocha M. Generative Deep Learning for Targeted Compound Design. J. Chem. Inf. Model. 2021; 61: 5343–5361. [CrossRef] [PubMed]
14. Rajalingham R.; Piccato A.; Jazayeri, M. Recurrent Neural Networks with Explicit Representation of Dynamic Latent Variables Can Mimic Behavioral Patterns in a Physical Inference Task. Nat. Commun. 2022; 13: 5865. [CrossRef]
15. Nag S.; Baidya A.T.K.; Mandal A.; Mathew A.T.; Das B.; Devi B.; Kumar R. Deep Learning Tools for Advancing Drug Discovery and Development. 3 Biotech 2022; 12: 110.
16. Liu X.; Liu C.; Huang R.; Zhu H.; Liu Q.; Mitra S.; Wang Y. Long Short-Term Memory Recurrent Neural Network for Pharmacokinetic-Pharmacodynamic Modeling. Int. J. Clin. Pharmacol. Ther. 2021; 59: 138–146. [CrossRef]
17. Turchin A.; Masharsky S.; Zitnik, M. Comparison of BERT Implementations for Natural Language Processing of Narrative Medical Documents. Inform. Med. Unlocked 2023; 36: 101139. [CrossRef]
18. Huo L.; Tang Y. Multi-Objective Deep Reinforcement Learning for Personalized Dose Optimization Based on Multi-Indicator Experience Replay. Appl. Sci. 2022; 13: 325. [CrossRef]
19. Olivier A.; Shields M.D.; Graham-Brady L. Bayesian Neural Networks for Uncertainty Quantification in Data-Driven Materials Modeling. Comput. Methods Appl. Mech. Eng. 2021; 386: 114079. [CrossRef]
20. Magris M.; Iosifidis A. Bayesian Learning for Neural Networks: An Algorithmic Survey. Artif. Intell. Rev. 2023. [CrossRef]
21. Pham T.-H.; Qiu Y.; Zeng J.; Xie L.; Zhang P. A Deep Learning Framework for High-Throughput Mechanism-Driven Phenotype Compound Screening and Its Application to COVID-19 Drug Repurposing. Nat. Mach. Intell. 2021; 3: 247–257. [CrossRef]
22. Meyers J.; Fabian B.; Brown N. De Novo Molecular Design and Generative Models. Drug Discov. Today 2021; 26: 2707–2715. [CrossRef] [PubMed]
23. Khadela A.; Popat S.; Ajabiya J.; Valu D.; Savale S.; Chavda V.P. AI, ML and Other Bioinformatics Tools for Preclinical and Clinical Development of Drug Products. In Bioinformatics Tools for

Pharmaceutical Drug Product Development; Wiley: Hoboken, NJ, USA, 2023; pp. 255–284. ISBN 978-1-119-86572-8.
24. Koutroumpa N.-M.; Papavasileiou K.D.; Papadiamantis A.G.; Melagraki G.; Afantitis A. A Systematic Review of Deep Learning Methodologies Used in the Drug Discovery Process with Emphasis on In Vivo Validation. Int. J. Mol. Sci. 2023; 24: 6573. [CrossRef]
25. Tang M.; Li B.; Chen H. Application of Message Passing Neural Networks for Molecular Property Prediction. Curr. Opin. Struct. Biol. 2023; 81: 102616. [CrossRef]
26. Reiser P.; Neubert M.; Eberhard A.; Torresi L.; Zhou C.; Shao C.; Metni H.; van Hoesel C.; Schopmans H.; Sommer T.; et al. Graph Neural Networks for Materials Science and Chemistry. Commun. Mater. 2022; 3: 93.
27. Chavda V.P. Nanotherapeutics and Nanobiotechnology. In Applications of Targeted Nano Drugs and Delivery Systems; Elsevier: Amsterdam, The Netherlands, 2019; pp. 1–13.
28. Colombo S. Applications of Artificial Intelligence in Drug Delivery and Pharmaceutical Development. In Artificial Intelligence in Healthcare; Elsevier: Amsterdam, The Netherlands, 2020; pp. 85–116.
29. Jiang J.; Ma X.; Ouyang D.; Williams R.O. Emerging Artificial Intelligence (AI) Technologies Used in the Development of Solid Dosage Forms. Pharmaceutics 2022; 14: 2257.
30. Han R.; Xiong H.; Ye Z.; Yang Y.; Huang T.; Jing Q.; Lu J.; Pan H.; Ren F.; Ouyang D. Predicting Physical Stability of Solid Dispersions by Machine Learning Techniques. J. Control. Release 2019; 311: 16–25.
31. Bannigan P.; Aldeghi M.; Bao Z.; Häse F.; Aspuru-Guzik A.; Allen C. Machine Learning Directed Drug Formulation Development. Adv. Drug Deliv. Rev. 2021; 175: 113806. [CrossRef]
32. Sun Y.; Peng Y.; Chen Y.; Shukla A.J. Application of Artificial Neural Networks in the Design of Controlled Release Drug Delivery Systems. Adv. Drug Deliv. Rev. 2003; 55: 1201–1215. [CrossRef]
33. Mukhamediev R.I.; Popova Y.; Kuchin Y.; Zaitseva E.; Kalimoldayev A.; Symagulov A.; Levashenko V.; Abdoldina F.; Gopejenko V.; Yakunin K.; et al. Review of Artificial Intelligence and Machine Learning Technologies: Classification, Restrictions, Opportunities and Challenges. Mathematics 2022; 10: 2552. [CrossRef]
34. Sengupta S.; Basak S.; Peters R. Particle Swarm Optimization: A Survey of Historical and Recent Developments with Hybridization Perspectives. Mach. Learn. Knowl. Extr. 2018; 1: 157–191. [CrossRef]
35. Paul D.; Sanap G.; Shenoy S.; Kalyane D.; Kalia K.; Tekade R.K. Artificial Intelligence in Drug Discovery and Development. Drug Discov. Today 2021; 26: 80–93.
36. Eberle L.G.; Sugiyama H.; Schmidt R. Improving Lead Time of Pharmaceutical Production Processes Using Monte Carlo Simulation. Comput. Chem. Eng. 2014; 68: 255–263.
37. Böhling P.; Khinast J.G.; Jajcevic D.; Davies C.; Carmody A.; Doshi P.; Am Ende M.T.; Sarkar, A. Computational Fluid Dynamics-Discrete Element Method Modeling of an Industrial-Scale Wurster Coater. J. Pharm. Sci. 2019; 108: 538–550. [CrossRef]
38. Song Y.; Zhou T.; Bai R.; Zhang M.; Yang H. Review of CFD-DEM Modeling of Wet Fluidized Bed Granulation and Coating Processes. Processes 2023; 11: 382. [CrossRef]
39. Mahapatra A.P.K.; Saraswat R.; Botre M.; Paul B.; Prasad N. Application of Response Surface Methodology (RSM) in Statistical Optimization and Pharmaceutical Characterization of a Patient Compliance Effervescent Tablet Formulation of an Antiepileptic Drug Levetiracetam. Future J. Pharm. Sci. 2020; 6: 82. [CrossRef]
40. Malakar, J.; Nayak, A.K.; Goswami, S. Use of Response Surface Methodology in the Formulation and Optimization of Bisoprolol Fumarate Matrix Tablets for Sustained Drug Release. ISRN Pharm. 2012; 2012: 730624. [CrossRef] [PubMed]
41. Madgulkar A.; Bhalekar M.; Kolhe V.; Kenjale Y. Formulation and Optimization of Sustained Release Tablets of Venlafaxine Resinates Using Response Surface Methodology. Indian J. Pharm. Sci. 2009; 71: 387. [CrossRef] [PubMed]
42. Kundu P.; Paul V.; Kumar V.; Mishra I.M. Formulation Development, Modeling and Optimization of Emulsification Process Using Evolving RSM Coupled Hybrid ANN-GA Framework. Chem. Eng. Res. Des. 2015; 104: 773–790.
43. Alhijjaj M.; Nasereddin J.; Belton P.; Qi S. Impact of Processing Parameters on the Quality of Pharmaceutical Solid Dosage Forms Produced by Fused Deposition Modeling (FDM). Pharmaceutics 2019; 11: 633.

44. Yost E.; Chalus P.; Zhang S.; Peter S.; Narang A.S. Quantitative X-Ray Microcomputed Tomography Assessment of Internal Tablet Defects. J. Pharm. Sci. 2019; 108: 1818–1830
45. Das K.P.; Chandra J. Nanoparticles and Convergence of Artificial Intelligence for Targeted Drug Delivery for Cancer Therapy: Current Progress and Challenges. Front. Med. Technol. 2023; 4: 1067144. [CrossRef]
46. Villa Nova M.; Lin T.P.; Shanehsazzadeh S.; Jain K.; Ng S.C.Y.; Wacker R.; Chichakly K.; Wacker M.G. Nanomedicine Ex Machina: Between Model-Informed Development and Artificial Intelligence. Front. Digit. Health 2022; 4: 799341.
47. Mohan B.; Kamaraj R.; Navyaja K. Role of Artificial Intelligence in Parenteral Formulation: A Review. ECS Trans. 2022; 107: 20013–20020.