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# Artificial Intelligence in Drug Discovery: Transforming Pharmaceutical Research and Development

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***Abstract:*** ***Artificial Intelligence (AI) has emerged as a transformative force in drug discovery, addressing the limitations of traditional pharmaceutical research methods. Conventional drug development is a lengthy, costly, and high-risk process, often taking more than a decade with significant financial investment. AI technologies, including machine learning, deep learning, and data analytics, enable rapid processing of vast biological and chemical datasets, thereby accelerating the identification of potential drug candidates and improving decision-making throughout the discovery pipeline.***
***AI applications span multiple stages of drug discovery, including target identification, virtual screening, lead optimization, and clinical trial design. By leveraging predictive models and pattern recognition, AI enhances the accuracy of molecular interactions, toxicity prediction, and pharmacokinetic profiling. Furthermore, AI-driven approaches facilitate drug repurposing, reducing development timelines and costs. The integration of AI with bioinformatics and cheminformatics has significantly improved efficiency, productivity, and success rates in pharmaceutical research.***
***Despite its advantages, the implementation of AI in drug discovery faces challenges such as data quality issues, lack of interpretability, and regulatory concerns. However, ongoing advancements in computational power and algorithm development continue to overcome these limitations. AI is expected to play a pivotal role in the future of personalized medicine and precision therapeutics, ultimately revolutionizing the pharmaceutical industry and improving global healthcare outcomes.***
***Keywords: Artificial Intelligence, Drug Discovery, Machine Learning, Deep Learning, Virtual Screening, Drug Repurposing, Computational Biology, Pharmaceutical Research.***

## I. INTRODUCTION

Drug discovery is a fundamental component of pharmaceutical sciences aimed at identifying new therapeutic agents for the prevention, management, and treatment of diseases. Traditionally, this process has been highly complex, time-consuming, and expensive, often taking 10–15 years and costing billions of dollars to bring a single drug to market. The conventional pipeline involves multiple stages, including target identification, hit discovery, lead optimization, preclinical studies, and clinical trials. Despite significant scientific advancements, the overall success rate of drug candidates remains low, with a high proportion of compounds failing during late-stage clinical trials due to issues related to efficacy, toxicity, or pharmacokinetics. These limitations highlight the urgent need for more efficient and reliable approaches in drug discovery.

In recent years, Artificial Intelligence (AI) has emerged as a powerful tool capable of transforming the traditional drug discovery paradigm. AI encompasses a range of computational techniques, including machine learning (ML), deep learning (DL), and natural language processing (NLP), which enable systems to learn from large datasets, identify patterns, and make predictions with minimal human intervention. The rapid growth of biological data—such as genomics, proteomics, metabolomics, and high-throughput screening results—has created an ideal environment for AI-driven methodologies. By integrating and analyzing these vast datasets, AI can uncover hidden relationships between biological targets and chemical compounds, thereby accelerating the identification of promising drug candidates. One of the most significant contributions of AI in drug discovery lies in its ability to enhance target identification and validation. AI algorithms can analyze complex biological networks to identify disease-associated genes and proteins, providing insights into novel therapeutic targets. Additionally, advances in deep learning have enabled accurate prediction of protein structures, which is crucial for understanding molecular interactions and designing effective drugs. AI also plays a vital role in virtual screening, where millions of compounds can be evaluated computationally to identify those with the highest likelihood of binding to a specific target, significantly reducing the need for costly and time-intensive laboratory experiments.

Furthermore, AI has revolutionized lead optimization by enabling the prediction of physicochemical properties, biological activity, and toxicity of drug candidates. Machine learning models can suggest structural modifications to improve drug efficacy and safety profiles, thereby increasing the chances of success in later stages. AI-driven approaches are also widely used in drug repurposing, where existing drugs are analyzed for new therapeutic indications, offering a faster and more cost-effective alternative to de novo drug development. This approach gained particular attention during global health emergencies, such as the COVID-19 pandemic, where rapid identification of effective treatments was critical.

In addition to early-stage discovery, AI is increasingly being applied to clinical development. It aids in optimizing clinical trial design, improving patient recruitment, and predicting treatment outcomes. AI-powered tools can analyze electronic health records and real-world data to identify suitable patient populations, thereby enhancing trial efficiency and reducing attrition rates. Moreover, AI contributes to personalized medicine by enabling the development of tailored therapies based on individual genetic and molecular profiles, ultimately improving treatment outcomes and minimizing adverse effects.

Despite its transformative potential, the integration of AI into drug discovery is not without challenges. Issues such as data quality, data privacy, lack of standardization, and limited interpretability of AI models remain significant barriers. Regulatory frameworks for AI-based drug development are still evolving, and there is a need for greater transparency and validation of AI-generated results. Additionally, interdisciplinary collaboration between computational scientists, biologists, chemists, and clinicians is essential to fully harness the benefits of AI technologies.

In conclusion, Artificial Intelligence is reshaping the landscape of drug discovery by providing innovative solutions to longstanding challenges in pharmaceutical research. Its ability to process large-scale data, predict complex biological interactions, and optimize decision-making processes positions AI as a critical tool in the development of safer, more effective, and affordable medicines. As technological advancements continue and challenges are addressed, AI is expected to play an increasingly central role in the future of drug discovery and healthcare innovation.

## II. OVERVIEW OF ARTIFICIAL INTELLIGENCE

Artificial Intelligence (AI) refers to the simulation of human intelligence by computer systems that are capable of learning, reasoning, problem-solving, and decision-making. In the context of pharmaceutical research, AI enables the analysis of complex biological and chemical data to generate meaningful insights that support drug discovery and development. AI systems are designed to process large volumes of structured and unstructured data, identify patterns, and make predictions with high accuracy, thereby enhancing efficiency and reducing human intervention.

AI encompasses several subfields, among which machine learning (ML) is one of the most widely used in drug discovery. Machine learning involves algorithms that learn from historical data and improve their performance over time without being explicitly programmed. It includes supervised learning (using labeled data), unsupervised learning (identifying hidden patterns in unlabeled data), and reinforcement learning (learning through trial and error). These approaches are particularly useful in predicting molecular properties, biological activity, and drug-target interactions.

Another important component of AI is deep learning (DL), a subset of machine learning that uses artificial neural networks inspired by the structure and function of the human brain. Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are highly effective in handling complex datasets like protein structures, genomic sequences, and medical imaging data. These models can automatically extract relevant features from raw data, making them especially powerful for tasks such as protein structure prediction, virtual screening, and toxicity assessment.

Natural Language Processing (NLP) is another significant branch of AI that focuses on enabling machines to understand and interpret human language. In drug discovery, NLP is used to extract valuable information from scientific literature, clinical trial reports, patents, and electronic health records. This helps researchers stay updated with the latest findings, identify potential drug candidates, and uncover previously overlooked relationships between diseases and therapeutic agents.

AI also integrates with big data analytics and cloud computing, which provide the infrastructure needed to store, manage, and process vast amounts of biomedical data. The availability of high-throughput technologies, such as next-generation sequencing and high-content screening, has led to an exponential increase in data generation. AI tools leverage this data to build predictive models that support decision-making at various stages of drug discovery.

In addition, AI systems often employ computer-aided drug design (CADD) techniques, combining computational chemistry with intelligent algorithms to model molecular interactions and optimize drug candidates. These systems can simulate how a drug interacts with its biological target, predict binding affinities, and suggest structural modifications to improve efficacy and reduce adverse effects.

Despite its numerous advantages, AI has certain limitations, including dependence on high-quality data, potential biases in algorithms, and challenges in model interpretability. Nevertheless, continuous advancements in computational power, algorithm development, and data availability are addressing these issues, making AI an indispensable tool in modern pharmaceutical research.

## III. DRUG DISCOVERY PROCESS

The drug discovery process is a multi-step, systematic approach aimed at identifying and developing new therapeutic agents. Each stage plays a critical role in ensuring the safety, efficacy, and quality of the final drug product.

### *A. Target Identification*

Target identification is the initial step in drug discovery, where a biological molecule (such as a protein, gene, or receptor) associated with a disease is identified. The goal is to select a target whose modulation can produce a therapeutic effect. This process involves the use of genomics, proteomics, and bioinformatics tools to understand disease mechanisms at the molecular level. Researchers analyze disease pathways and identify key molecules involved in disease progression. With advancements in AI and computational biology, large datasets can be analyzed efficiently to identify novel and previously unknown targets.

### *B. Target Validation*

Once a potential target is identified, it must be validated to confirm its role in the disease and its suitability for drug intervention. Target validation ensures that modifying the target will have the desired therapeutic effect without causing significant adverse effects. This is achieved through in vitro studies (cell-based assays), in vivo studies (animal models), and genetic approaches such as gene knockdown or overexpression. Successful validation increases confidence that the target is biologically relevant and druggable.

### *C. Lead Compound Identification*

In this stage, compounds that interact with the validated target are identified. These compounds, known as “hits,” are discovered through methods such as high-throughput screening (HTS), virtual screening, and fragment-based drug discovery. Researchers screen thousands to millions of chemical compounds to find those that show promising activity against the target. These initial hits are then refined into “lead compounds,” which demonstrate better potency and selectivity. AI tools significantly enhance this process by rapidly screening vast chemical libraries and predicting potential interactions.

### *D. Lead Optimization*

Lead optimization involves modifying the chemical structure of lead compounds to improve their pharmacological properties. The objective is to enhance potency, selectivity, safety, and pharmacokinetic properties such as absorption, distribution, metabolism, and excretion (ADME). Medicinal chemists make systematic changes to the molecular structure and evaluate their effects through experimental and computational methods. This stage is iterative and may involve multiple rounds of design, synthesis, and testing to achieve an optimal candidate with minimal toxicity and maximum efficacy.

### *E. Preclinical Testing*

Preclinical testing is conducted to evaluate the safety and biological activity of the optimized drug candidate before it is tested in humans. This stage includes both in vitro (cell culture) and in vivo (animal) studies. Researchers assess pharmacodynamics (drug effects), pharmacokinetics (drug movement in the body), toxicity, and dose-response relationships. Regulatory guidelines require extensive safety evaluation to ensure that the drug does not pose significant risks. Only candidates that demonstrate acceptable safety and efficacy profiles proceed to clinical trials.

### *F. Clinical Trials*

Clinical trials are conducted in human subjects to evaluate the safety, efficacy, and optimal dosage of the drug. This stage is divided into multiple phases:

1) Phase I: Conducted on a small group of healthy volunteers to assess safety, tolerability, and pharmacokinetics.
2) Phase II: Conducted on patients to evaluate efficacy and determine optimal dosing while continuing safety assessments.
3) Phase III: Large-scale studies involving a larger patient population to confirm efficacy, monitor side effects, and compare with existing treatments.
4) Phase IV (Post-marketing): Conducted after regulatory approval to monitor long-term safety and effectiveness.

Clinical trials are the most time-consuming and expensive part of drug development, with strict regulatory and ethical requirements.

### G. Regulatory Approval

After successful clinical trials, the drug developer submits a comprehensive dossier to regulatory authorities for approval. This includes all data related to preclinical studies, clinical trials, manufacturing processes, and quality control. Regulatory agencies such as the U.S. Food and Drug Administration and the Central Drugs Standard Control Organization evaluate the data to ensure that the drug is safe, effective, and of high quality. If approved, the drug is authorized for marketing and distribution. Post-approval surveillance continues to monitor adverse effects and ensure ongoing safety.

## IV. APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN DRUG DISCOVERY

Artificial Intelligence (AI) has significantly transformed the drug discovery landscape by enhancing speed, accuracy, and efficiency across various stages of the process. Its ability to analyze vast datasets and identify complex patterns makes it an invaluable tool in modern pharmaceutical research. The key applications of AI in drug discovery are discussed below:

### A. Target Identification and Validation

AI algorithms analyze large-scale biological data, including genomics, proteomics, and transcriptomics, to identify potential drug targets associated with specific diseases. Machine learning models can uncover hidden relationships between genes, proteins, and disease pathways, enabling researchers to identify novel therapeutic targets. Additionally, AI helps in validating these targets by predicting their biological relevance and druggability, thereby reducing the risk of failure in later stages.

### B. Virtual Screening

Virtual screening involves the computational evaluation of large libraries of chemical compounds to identify potential drug candidates. AI-driven models can rapidly predict how different molecules will interact with a target protein, significantly reducing the need for physical screening. This approach saves time, lowers costs, and increases the efficiency of hit identification compared to traditional high-throughput screening methods.

### C. Lead Identification and Optimization

AI plays a crucial role in both identifying lead compounds and optimizing them for better performance. Machine learning models can predict the biological activity, toxicity, and pharmacokinetic properties of compounds. AI also suggests structural modifications to improve efficacy, selectivity, and safety. This reduces the number of experimental iterations required and accelerates the development of promising drug candidates.

### D. Drug Repurposing

Drug repurposing involves finding new therapeutic uses for existing drugs. AI analyzes clinical data, molecular structures, and disease pathways to identify potential new indications for approved or investigational drugs. This approach significantly reduces development time and cost, as repurposed drugs have already undergone safety testing. AI-driven drug repurposing gained significant importance during global health crises due to its rapid response capabilities.

### E. Prediction of Drug-Drug Interactions and Toxicity

AI models can predict potential drug-drug interactions and adverse effects by analyzing chemical structures and biological data. This helps in identifying safety issues early in the drug development process, reducing the likelihood of failure during clinical trials. Predictive toxicology using AI ensures safer drug candidates and minimizes risks to patients.

### F. De Novo Drug Design

AI enables the design of entirely new drug molecules from scratch using generative models such as deep neural networks. These models can create novel chemical structures with desired properties, such as high binding affinity and low toxicity. This approach expands the chemical space and allows researchers to discover innovative compounds that may not be identified through traditional methods.

*G. Clinical Trial Optimization*

AI improves the efficiency of clinical trials by optimizing study design, patient selection, and data analysis. It can analyze electronic health records and real-world data to identify suitable patient populations, predict patient responses, and reduce dropout rates. This leads to faster and more successful clinical trials with improved outcomes.

*H. Personalized Medicine*

AI facilitates the development of personalized therapies by analyzing individual patient data, including genetic profiles, lifestyle factors, and disease characteristics. This enables the design of targeted treatments tailored to individual patients, improving therapeutic efficacy and reducing adverse effects.

## V. ADVANTAGES OF ARTIFICIAL INTELLIGENCE IN DRUG DISCOVERY

The integration of Artificial Intelligence (AI) into drug discovery has brought numerous advantages that address the limitations of traditional pharmaceutical research. These benefits contribute to faster, more cost-effective, and highly efficient drug development processes.

*A. Reduction in Time and Cost*

One of the most significant advantages of AI is its ability to drastically reduce the time and cost associated with drug discovery. Traditional drug development can take over a decade and require substantial financial investment. AI accelerates various stages such as target identification, virtual screening, and lead optimization by rapidly analyzing large datasets. This reduces the need for extensive laboratory experiments and shortens the overall development timeline.

*B. Improved Accuracy and Predictability*

AI models can analyze complex biological and chemical data with high precision, leading to more accurate predictions of drug behavior. Machine learning algorithms can predict drug-target interactions, toxicity, and pharmacokinetic properties, thereby improving decision-making. This reduces the likelihood of failure in later stages of development, particularly during clinical trials.

*C. Enhanced Data Handling Capabilities*

Drug discovery involves the generation and analysis of massive amounts of data from sources such as genomics, proteomics, and clinical studies. AI can efficiently process and integrate these large datasets, identifying patterns and relationships that may not be apparent through traditional methods. This capability enhances the understanding of disease mechanisms and supports the discovery of novel drug candidates.

*D. Increased Success Rate*

By improving target selection, optimizing lead compounds, and predicting potential failures early in the process, AI increases the overall success rate of drug development. Early identification of ineffective or toxic compounds reduces attrition rates and ensures that only the most promising candidates progress to clinical trials.

*E. Automation of Repetitive Tasks*

AI automates many repetitive and time-consuming tasks such as data analysis, compound screening, and documentation. This allows researchers to focus on more complex and strategic aspects of drug development. Automation also minimizes human error and increases consistency in research outcomes.

*F. Facilitation of Drug Repurposing*

AI enables efficient identification of new therapeutic uses for existing drugs by analyzing biological data and disease pathways. Drug repurposing significantly reduces development time, cost, and risk, as the safety profiles of these drugs are already established.

*G. Support for Personalized Medicine*

AI plays a crucial role in advancing personalized medicine by analyzing patient-specific data such as genetic information and medical history. This allows for the development of targeted therapies tailored to individual patients, improving treatment outcomes and minimizing adverse effects.

*H. Better Decision-Making*

AI provides data-driven insights that support informed decision-making at every stage of drug discovery. Predictive models help researchers prioritize the most promising drug candidates, optimize experimental design, and allocate resources more effectively.

In conclusion, Artificial Intelligence offers substantial advantages in drug discovery by enhancing efficiency, accuracy, and innovation. Its ability to streamline processes, reduce costs, and improve success rates makes it an indispensable tool in modern pharmaceutical research.

## VI. DISADVANTAGES AND LIMITATIONS OF ARTIFICIAL INTELLIGENCE IN DRUG DISCOVERY

Despite its transformative potential, the application of Artificial Intelligence (AI) in drug discovery is associated with several challenges and limitations. Understanding these drawbacks is essential for the effective and responsible implementation of AI in pharmaceutical research.

*A. Dependence on High-Quality Data*

AI models rely heavily on large volumes of high-quality, well-structured data. In drug discovery, data may be incomplete, inconsistent, or biased, which can lead to inaccurate predictions. Poor data quality directly affects the performance and reliability of AI systems, making data curation and validation a critical challenge.

*B. Lack of Interpretability (Black Box Problem)*

Many AI models, particularly deep learning algorithms, function as “black boxes,” meaning their decision-making processes are not easily interpretable. This lack of transparency makes it difficult for researchers and regulatory authorities to fully understand how predictions are generated, which can hinder trust and acceptance in critical applications like drug development.

*C. High Implementation Cost*

Although AI reduces long-term costs, the initial investment required for implementing AI systems can be very high. This includes expenses related to infrastructure, software, data acquisition, and skilled personnel. Smaller pharmaceutical companies and research institutions may find it challenging to adopt AI technologies due to these financial constraints.

*D. Requirement of Specialized Expertise*

The successful application of AI in drug discovery requires interdisciplinary expertise, including knowledge of computer science, bioinformatics, chemistry, and pharmacology. There is a shortage of professionals with such combined skills, which can limit the effective utilization of AI tools.

*E. Data Privacy and Security Concerns*

AI systems often rely on sensitive data, such as patient health records and clinical trial information. Ensuring data privacy and compliance with regulatory standards is a major challenge. Unauthorized access or data breaches can have serious ethical and legal consequences.

*F. Limited Generalization Ability*

AI models are typically trained on specific datasets and may not perform well when applied to new or unseen data. This limitation, known as poor generalization, can reduce the reliability of AI predictions in diverse biological systems or different patient populations.

*G. Regulatory and Ethical Challenges*

The integration of AI into drug discovery raises regulatory and ethical concerns. Current regulatory frameworks are not fully equipped to evaluate AI-generated results, leading to uncertainties in approval processes. Ethical issues such as algorithmic bias and accountability also need to be addressed.

*H. Risk of Over-Reliance on AI*

Excessive dependence on AI may reduce critical human judgment in decision-making. While AI provides valuable insights, it cannot completely replace human expertise, intuition, and experimental validation. Over-reliance on AI could lead to errors if predictions are not carefully verified.

### *I. Integration with Existing Systems*

Incorporating AI into existing drug discovery workflows can be challenging due to compatibility issues with legacy systems and lack of standardization. This may require significant restructuring of current processes and infrastructure.

In conclusion, while Artificial Intelligence offers numerous advantages in drug discovery, it also presents several limitations that must be carefully managed. Addressing these challenges through improved data quality, transparent algorithms, regulatory frameworks, and interdisciplinary collaboration will be essential for maximizing the potential of AI in pharmaceutical research.

## VII. CONCLUSION

Artificial Intelligence (AI) has emerged as a powerful and transformative technology in the field of drug discovery, addressing many of the limitations associated with traditional pharmaceutical research. By integrating advanced computational techniques such as machine learning, deep learning, and data analytics, AI has significantly enhanced the efficiency, speed, and accuracy of the drug development process. From target identification and virtual screening to lead optimization and clinical trial design, AI is playing a critical role at every stage of the drug discovery pipeline.

The adoption of AI has led to substantial reductions in time and cost, improved prediction of drug efficacy and safety, and increased overall success rates. Its ability to analyze vast and complex biological datasets has enabled the identification of novel drug targets and the discovery of innovative therapeutic compounds. Additionally, AI-driven approaches such as drug repurposing and personalized medicine have opened new avenues for faster and more effective treatment strategies, ultimately improving patient outcomes and advancing global healthcare.

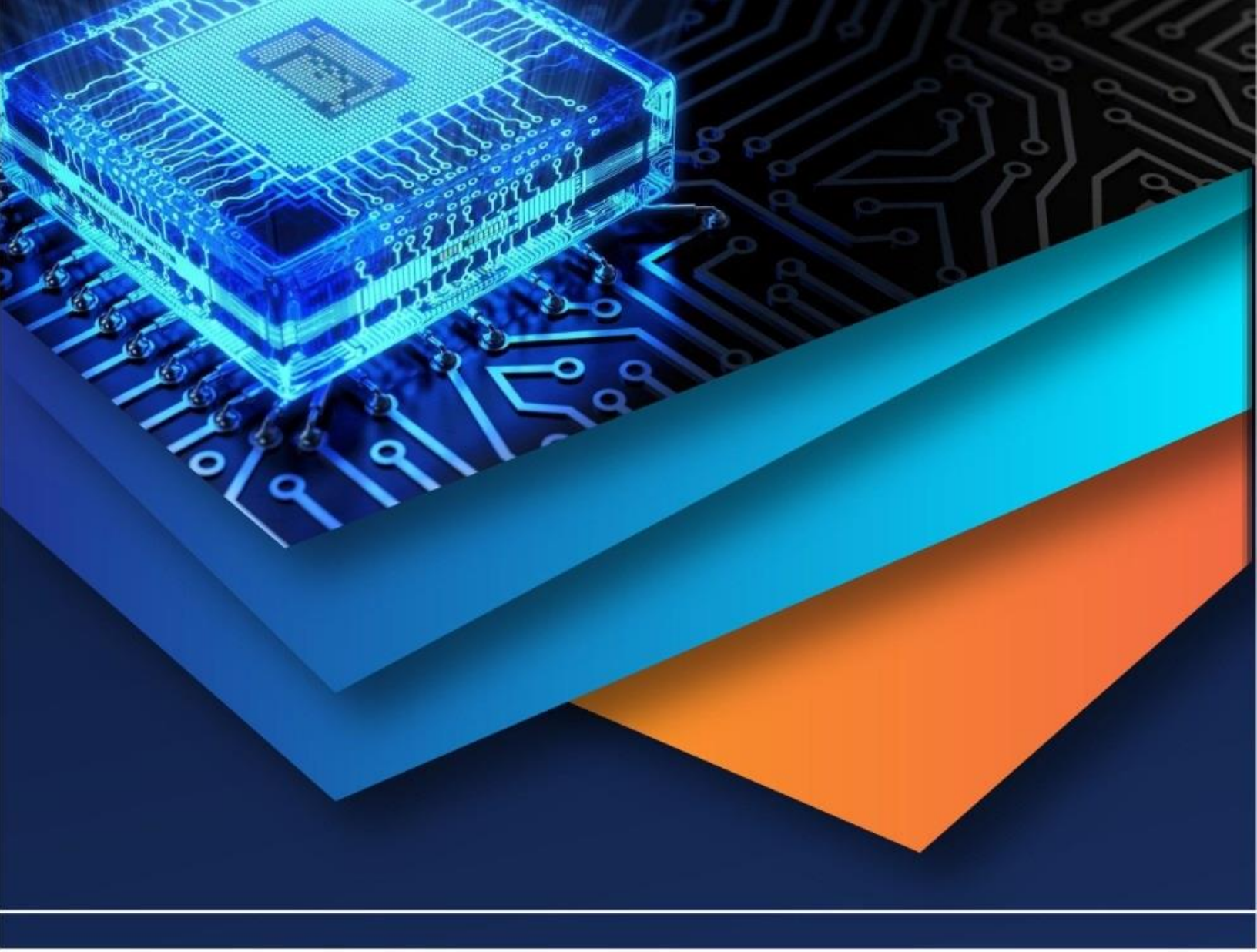
However, despite its numerous advantages, AI in drug discovery is not without challenges. Issues related to data quality, model interpretability, regulatory uncertainty, and the need for specialized expertise remain significant barriers to its widespread implementation. Ethical concerns, including data privacy and algorithmic bias, must also be carefully addressed to ensure responsible use of AI technologies. Furthermore, AI should be viewed as a complementary tool rather than a replacement for human expertise, as experimental validation and scientific judgment remain essential components of drug development.

Looking forward, continuous advancements in computational power, availability of high-quality data, and the development of more transparent and robust AI models are expected to overcome current limitations. Collaborative efforts between researchers, pharmaceutical industries, regulatory authorities, and technology experts will be crucial in fully harnessing the potential of AI. In the coming years, AI is poised to play a central role in shaping the future of drug discovery, leading to the development of safer, more effective, and affordable medicines, and ultimately revolutionizing the healthcare landscape.

## REFERENCES

[1] Aliper, A., Plis, S., Artemov, A., Ulloa, A., Mamoshina, P., & Zhavoronkov, A. (2016). Deep learning applications for predicting pharmacological properties of drugs. Molecular Pharmaceutics, 13(7), 2524–2530.
[2] Baskin, I. I. (2020). The power of deep learning to ligand-based drug discovery. Expert Opinion on Drug Discovery, 15(7), 755–764.
[3] Chen, H., Engkvist, O., Wang, Y., Olivecrona, M., & Blaschke, T. (2018). The rise of deep learning in drug discovery. Drug Discovery Today, 23(6), 1241–1250.
[4] Ekins, S. (2016). The next era: Deep learning in pharmaceutical research. Pharmaceutical Research, 33(11), 2594–2603.
[5] Gawehn, E., Hiss, J. A., & Schneider, G. (2016). Deep learning in drug discovery. Molecular Informatics, 35(1), 3–14.
[6] Goh, G. B., Hodas, N. O., & Vishnu, A. (2017). Deep learning for computational chemistry. Journal of Computational Chemistry, 38(16), 1291–1307.
[7] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.
[8] Jiménez-Luna, J., Grisoni, F., & Schneider, G. (2020). Drug discovery with explainable AI. Nature Machine Intelligence, 2(10), 573–584.
[9] Jumper, J., Evans, R., Pritzel, A., et al. (2021). Highly accurate protein structure prediction with AlphaFold. Nature, 596, 583–589.
[10] Kearnes, S., McCloskey, K., Berndl, M., et al. (2016). Molecular graph convolutions. Journal of Computer-Aided Molecular Design, 30, 595–608.
[11] Kingma, D. P., & Welling, M. (2014). Auto-encoding variational Bayes. International Conference on Learning Representations.
[12] Lavecchia, A. (2015). Machine-learning approaches in drug discovery. Drug Discovery Today, 20(3), 318–331.
[13] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444.
[14] Mak, K. K., & Pichika, M. R. (2019). Artificial intelligence in drug development. Drug Discovery Today, 24(3), 773–780.
[15] Mamoshina, P., Vieira, A., Putin, E., & Zhavoronkov, A. (2016). Applications of deep learning in biomedicine. Molecular Pharmaceutics, 13(5), 1445–1454.
[16] Mater, A. C., & Coote, M. L. (2019). Deep learning in chemistry. Journal of Chemical Information and Modeling, 59(6), 2545–2559.
[17] Mendez, D., Gaulton, A., Bento, A. P., et al. (2019). ChEMBL database. Nucleic Acids Research, 47(D1), D930–D940.
[18] Paul, D., Sanap, G., Shenoy, S., et al. (2021). Artificial intelligence in drug discovery. Drug Discovery Today, 26(1), 80–93.
[19] Popova, M., Isayev, O., & Tropsha, A. (2018). Deep reinforcement learning for de novo drug design. Science Advances, 4(7), eaap7885.
[20] Ramsundar, B., Eastman, P., Walters, P., et al. (2019). Deep learning for the life sciences. O'Reilly Media.

[21] Schneider, G. (2018). Automating drug discovery. Nature Reviews Drug Discovery, 17(2), 97–113.
[22] Segler, M. H. S., Preuss, M., & Waller, M. P. (2018). Planning chemical syntheses with AI. Nature, 555, 604–610.
[23] Stokes, J. M., Yang, K., Swanson, K., et al. (2020). AI-discovered antibiotic. Cell, 180(4), 688–702.
[24] Vamathevan, J., Clark, D., Czodrowski, P., et al. (2019). Applications of ML in drug discovery. Nature Reviews Drug Discovery, 18, 463–477.
[25] Walters, W. P., & Murcko, M. (2020). AI in medicinal chemistry. Nature Biotechnology, 38(2), 143–145.
[26] Zhavoronkov, A. (2018). AI for drug discovery. Nature Biotechnology, 36(11), 1038–1040.
[27] Brown, N. (2020). Chemoinformatics and AI. Future Medicinal Chemistry, 12(7), 593–596.
[28] Chen, B., Butte, A. J. (2016). Leveraging big data in drug discovery. Nature Reviews Drug Discovery, 15, 291–292.
[29] Ekins, S., & Freundlich, J. S. (2018). Machine learning in drug discovery. Pharmaceutical Research, 35, 1–6.
[30] Fleming, N. (2018). How AI is changing drug discovery. Nature, 557, S55–S57.
[31] Gorgulla, C., Boeszoermenyi, A., Wang, Z. F., et al. (2020). VirtualFlow platform. Nature, 580, 663–668.
[32] Hinton, G. (2018). Deep learning overview. Communications of the ACM, 61(11), 42–44.
[33] Koutsoukas, A., Simms, B., Kirchmair, J., et al. (2011). Machine learning in chemoinformatics. Journal of Chemical Information and Modeling, 51(3), 542–552.
[34] Lowe, D. (2017). AI in pharma industry. Science Translational Medicine, 9(380).
[35] Moffat, J. G., Vincent, F., Lee, J. A., et al. (2017). Opportunities in phenotypic drug discovery. Nature Reviews Drug Discovery, 16, 531–543.
[36] Olivecrona, M., Blaschke, T., Engkvist, O., & Chen, H. (2017). Molecular de novo design. Journal of Cheminformatics, 9(1), 48.
[37] Paul, S. M., Mytelka, D. S., Dunwiddie, C. T., et al. (2010). Drug development pipeline challenges. Nature Reviews Drug Discovery, 9, 203–214.
[38] Pereira, J. C., Caffarena, E. R., & dos Santos, C. N. (2016). Boosting docking with ML. Journal of Chemical Information and Modeling, 56(12), 2495–2506.
[39] Rifaioglu, A. S., Atas, H., Martin, M. J., et al. (2019). Deep learning in drug discovery. Bioinformatics, 35(19), 3743–3751.
[40] Schneider, P., Walters, W. P., & Plowright, A. T. (2020). Rethinking drug design with AI. Nature Reviews Drug Discovery, 19, 353–364.
[41] Sun, J., Jeliazkova, N., Chupakhin, V., et al. (2017). QSAR modeling.Molecular Informatics, 36(3).
[42] Tang, B., Pan, Z., Yin, K., & Khateeb, A. (2019). Deep learning in bioinformatics. Briefings in Bioinformatics, 20(5), 1681–1701.
[43] Turki, T., Wei, Z., Wang, J. T. L., & Zeng, J. (2019). ML in computational biology. IEEE/ACM Transactions, 16(4), 1017–1029.
[44] Vamathevan, J. (2018). ML in pharma. Nature Reviews Drug Discovery, 17, 463–477.
[45] Walters, W. P. (2019). Virtual chemical libraries. Journal of Medicinal Chemistry, 62(3), 1116–1124.
[46] Wójcikowski, M., Zielenkiewicz, P., & Siedlecki, P. (2015). Open drug discovery. Drug Discovery Today, 20(6), 744–751.
[47] Xu, Y., Pei, J., & Lai, L. (2017). Deep learning for drug discovery. Drug Discovery Today, 22(8), 1240–1248.
[48] Yang, X., Wang, Y., Byrne, R., Schneider, G., & Yang, S. (2019). AI in drug discovery. Chemical Reviews, 119(18), 10520–10594.
[49] Zhavoronkov, A., Ivanenkov, Y. A., Aliper, A., et al. (2019). AI-designed drugs. Nature Biotechnology, 37, 1038–1040.
[50] Zhou, Z. H. (2021). Machine learning. Springer.



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