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Artificial Intelligence in Clinical Practice: Unlocking New Horizons in Drug Repurposing for Disease Treatment

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Artificial intelligence (AI) has emerged as a transformative force in drug repurposing, offering innovative solutions to expedite the identification of new therapeutic uses for existing medications. This review explores the multifaceted applications of AI, particularly in the context of complex and rare diseases, where traditional drug development processes are often hindered by high costs and lengthy timelines. AI-driven methodologies, including machine learning (ML), deep learning (DL), and natural language processing (NLP), facilitate the analysis of vast datasets from clinical trials, electronic health records, and scientific literature, enabling researchers to uncover novel drug-disease relationships. The integration of AI with genomics and proteomics further enhances the precision of drug repurposing efforts by identifying genetic and proteomic markers that predict patient responses to therapies. Despite its potential, the field faces challenges related to data quality, regulatory hurdles, and the need for interdisciplinary collaboration among researchers, clinicians, and policymakers. This review highlights recent advancements in AI applications for drug repurposing, emphasizing their role in addressing unmet medical needs, particularly in rare diseases where treatment options are limited. By harnessing the capabilities of AI, the drug repurposing landscape is poised for significant transformation, ultimately leading to more efficient pathways for delivering effective therapies to patients.

Keywords: Artificial Intelligence, Drug Repurposing, Machine Learning, Precision Medicine, Genomic

1. Introduction

Artificial Intelligence (AI) has emerged as a transformative force in healthcare, reshaping how medical professionals diagnose, treat, and manage diseases (Li, Du, Liu, & Chen, 2021). By leveraging vast amounts of data, AI algorithms can identify patterns and insights that may not be readily apparent to human clinicians (Dasta, 1992). Predictive analytics is a powerful application of artificial intelligence (AI) in healthcare that utilizes advanced algorithms to analyze vast amounts of patient data (European Medicines Agency, 2020). By examining historical and real-time data, including demographics, medical histories, and treatment outcomes, AI can identify patterns and correlations that enable healthcare providers to anticipate disease outbreaks, predict patient outcomes, and optimize treatment responses. This capability is particularly crucial in managing chronic diseases and improving patient care. For instance, predictive models can forecast the likelihood of hospital readmissions or the onset of complications, allowing healthcare teams to implement timely interventions (Radanliev & De Roure, 2023). The integration of predictive analytics not only enhances clinical decision-making but also supports personalized medicine by tailoring treatments to individual patients based on their unique risk profiles. As the field continues to evolve, the potential for AI-driven predictive analytics to transform patient care and operational efficiency becomes increasingly evident (European Commission, 2020). AI-driven diagnostic tools represent a significant advancement in the accuracy and efficiency of medical imaging interpretation (Pudjihartono et al., 2022). Machine learning models are trained on extensive datasets of medical images, such as X-rays, MRIs, and CT scans, enabling them to recognize subtle patterns that may be indicative of various conditions (Pharma News Intelligence, n.d.). These tools assist radiologists and clinicians by providing second opinions and highlighting areas of concern that may require further investigation (Abubaker Bagabir et al., 2022). For example, AI algorithms can detect early signs of diseases like cancer or cardiovascular issues with a level of precision that often surpasses traditional methods. The use of these diagnostic tools not only accelerates the diagnostic process but also reduces the risk of human error, ultimately leading to better patient outcomes. As technology advances, the integration of AI into diagnostic workflows is expected to enhance the overall quality of care provided in clinical settings (Haug & Drazen, 2023). Personalized medicine is an innovative approach that leverages AI to tailor treatment plans based on individual patient characteristics, including genetic information, lifestyle factors, and environmental influences (TARS, n.d.). By analyzing comprehensive datasets that encompass genetic profiles and health histories, AI can identify which treatments are likely to be most effective for specific patients (Hautz et al., 2019). This customization is particularly beneficial in fields like oncology, where targeted therapies can be developed based on the molecular makeup of a patient's tumor (Davoudi et al., n.d.). Furthermore, personalized medicine aims to minimize adverse drug reactions by ensuring that patients receive therapies that align with their unique biological profiles. As research progresses, the potential for AI to facilitate personalized treatment strategies continues to expand, promising significant improvements in therapeutic efficacy and patient satisfaction (Gandhi & Sabik, 2014). AI plays a crucial role in enhancing operational efficiency within healthcare organizations by streamlining administrative tasks that traditionally consume significant time and resources(Ghai et al., 2022). Tasks such as scheduling appointments, managing billing processes, and maintaining electronic health records can be optimized through AI-driven solutions (Jiang et al., 2017). For instance, predictive algorithms can analyze patient flow data

to improve appointment scheduling and reduce wait times (Buch, Ahmed, & Maruthappu, 2018). Additionally, AI can assist in automating billing procedures by accurately coding services based on clinical documentation, thereby minimizing errors and expediting revenue cycles. By alleviating the administrative burden on healthcare providers, AI allows them to focus more on direct patient care and clinical responsibilities (Matheny, Whicher, & Thadaney Israni, 2020). This shift not only improves staff satisfaction but also enhances the overall patient experience by ensuring timely access to care and reducing operational costs for healthcare facilities (Berlyand et al., 2018).

Importance of Drug Repurposing in Clinical Practice

Drug repurposing, also known as drug repositioning or reprofiling, is the strategy of identifying new therapeutic uses for existing drugs.

Cost-Effectiveness: Cost-Effectiveness is a significant advantage of drug repurposing, particularly in an era where healthcare costs are under scrutiny. The traditional process of developing new drugs is notoriously lengthy and expensive, often taking 10 to 15 years and costing upwards of $2.6 billion before a drug reaches the market. This extensive timeline includes multiple phases of research, development, and clinical trials, each fraught with uncertainty and risk (Panch, Szolovits, & Atun, 2018). In contrast, drug repurposing utilizes existing safety and efficacy data from previously approved medications, which can significantly reduce both the time and financial investment required for clinical trials(Abhishek et al., 2024). By bypassing the early stages of drug development, researchers can focus on assessing the efficacy of these established drugs for new indications, leading to faster regulatory approvals—typically within 3 to 12 years—and at a cost that can be 50% to 60% lower than that of new drug development. This cost-effectiveness not only benefits pharmaceutical companies but also enhances patient access to potentially life-saving treatments (Vandenberg et al., 2020).

Rapid Response to Health Crises: Rapid Response to Health Crises is another critical aspect of drug repurposing that has gained prominence in recent years, particularly highlighted during the COVID-19 pandemic. In such emergencies, the urgency for effective treatments demands swift action, and drug repurposing provides a viable solution by identifying existing medications that can be quickly adapted for new therapeutic uses (Collins et al., 2021). For instance, several drugs initially developed for other conditions were repurposed under emergency authorization to treat COVID-19 patients. Remdesivir, originally designed for Ebola, and dexamethasone, an anti-inflammatory steroid, were both rapidly evaluated and deployed as treatment options during the pandemic(Dharmendra Bhati et al., 2024). This ability to leverage already approved medications allows healthcare systems to respond more effectively to emerging health threats, ensuring that patients receive timely interventions while minimizing the risks associated with developing entirely new drugs from scratch (Vollmer et al., 2020).

Addressing Unmet Medical Needs: Addressing Unmet Medical Needs is a fundamental motivation behind drug repurposing efforts (Beam & Kohane, 2018). Many diseases, particularly rare or neglected conditions, often lack effective treatments due to limited research investment and the challenges associated with developing new drugs. Drug repurposing offers a pathway to discover new therapeutic options for these patients by utilizing compounds that

have previously undergone clinical evaluation (Rivera et al., 2020). For example, existing medications may prove effective against rare diseases when tested in targeted studies, providing hope where none existed before. This strategy not only broadens the therapeutic arsenal available to clinicians but also enhances the quality of life for patients suffering from conditions that have historically been difficult to treat or manage (Crossnohere et al., 2022).

Minimized Risk: Minimized Risk is another compelling reason for the growing interest in drug repurposing within the pharmaceutical industry (Alotaibi et al., 2020). Since repurposed drugs have established safety profiles from prior clinical use, they generally carry lower risks compared to novel compounds that are entering clinical trials for the first time(Mangala et al., 2024). The known pharmacokinetics and pharmacodynamics of these drugs mean that researchers can anticipate how they will behave in the human body when used for new indications (Donzé et al., 2013). This established safety record allows for more straightforward regulatory pathways and can lead to quicker approvals for repurposed drugs. As a result, healthcare providers can offer these therapies with greater confidence in their safety and efficacy, ultimately benefiting patients who may otherwise face long waits for effective treatment options (Ansari et al., 2021).

AI's Role in Revolutionizing Drug Repurposing

The objective of this article is to explore how artificial intelligence is revolutionizing the field of drug repurposing (Amarasingham et al., 2014).

Data Mining: Data Mining is a critical application of artificial intelligence (AI) in the context of drug repurposing, enabling researchers to analyze vast datasets from multiple sources, including clinical trials, electronic health records (EHRs), and scientific literature (Nelson et al., 2019). This process involves the extraction of meaningful patterns and insights from complex and often unstructured data. AI algorithms can efficiently sift through millions of patient records and trial results to identify potential candidates for repurposing, significantly speeding up the discovery process (Liu & Rudd, 2023). For instance, by analyzing historical data on drug interactions and patient responses, AI can highlight existing medications that may have therapeutic effects on diseases that were not previously considered. This capability not only enhances the likelihood of finding effective treatments but also allows researchers to leverage existing safety data, thereby reducing the risks associated with introducing new drugs. As a result, data mining serves as a powerful tool in the quest for innovative therapeutic solutions, facilitating more informed decision-making in drug development (Han et al., 2022).

Predictive Modeling: Predictive Modeling further enhances the drug repurposing process by utilizing machine learning algorithms to forecast which existing drugs may be effective against new diseases (Zhang, Chen, & Li, 2021). These algorithms analyze various factors, including the mechanisms of action of drugs and their biological pathways, to identify potential matches between approved medications and emerging health conditions(Rohit Kumar Trivedi et al., 2024). For example, predictive models can evaluate how a drug designed to treat one condition might interact with biological targets associated with another disease, thereby uncovering novel therapeutic applications. This approach allows researchers to prioritize candidates based on their predicted efficacy and safety profiles, streamlining the repurposing process (Partin et al., 2023). Additionally, predictive modeling can help anticipate patient responses to treatments based on individual genetic and phenotypic characteristics, making it possible to

tailor therapies more precisely(Bhatt et al., 2022). By harnessing the power of predictive analytics, researchers can significantly accelerate the timeline for bringing effective treatments to market while minimizing costs and risks (Sjövall, Lanckohr, & Bracht, 2023).

Clinical Trial Optimization: Clinical Trial Optimization is another area where AI demonstrates its transformative potential in drug repurposing (Blasiak et al., 2022). AI technologies can optimize trial designs by identifying suitable patient populations and predicting outcomes based on real-time data analysis. By employing machine learning techniques, researchers can simulate various trial scenarios to determine the most effective methodologies for testing repurposed drugs(Sharma & Bhatt, 2021). This includes adjusting eligibility criteria to enhance participant recruitment or modifying treatment protocols based on interim results (Lee et al., 2021). AI-driven tools can also analyze historical trial data to identify trends and factors that contribute to successful outcomes, allowing for more informed decision-making in trial design. Furthermore, by predicting patient responses and potential adverse effects, AI helps ensure that trials are conducted more efficiently and ethically(Sharma & Singh, 2020). The ability to optimize clinical trials not only accelerates the development process for repurposed drugs but also improves the overall quality of clinical research, ultimately benefiting patients through faster access to innovative therapies (Martin et al., 2022;Sheu et al., 2023).

Table 1: Comparison of Traditional Drug Development vs. Drug Repurposing (Huang et al., 2018).

Feature	Traditional Drug Development	Drug Repurposing
Timeframe	10-15 years	3-5 years
Cost	$1 billion+	$300 million - $500 million
Regulatory Approval Process	Extensive (Phase I-IV trials)	Streamlined (often Phase II/III)
Risk Level	High	Lower due to established safety
Innovation Potential	High but uncertain	Moderate; relies on existing drugs
Examples of Successes	New chemical entities	Sildenafil (Viagra), Thalidomide

Drug Repurposing

Drug repurposing, also known as drug repositioning or reprofiling, refers to the strategy of identifying new therapeutic uses for existing drugs that have already been approved for other indications or are in various stages of clinical development. This approach is particularly significant in the context of urgent healthcare needs, where traditional drug discovery processes may be too slow or costly (Pulley et al., 2012). By leveraging the safety and efficacy data of established medications, researchers can quickly assess their potential for treating different diseases. The importance of drug repurposing lies in its ability to provide new treatment options for conditions that currently have limited therapies available, thereby enhancing patient care and addressing unmet medical needs. In recent years, especially during public health emergencies like the COVID-19 pandemic, the value of drug repurposing has been underscored, as it allows for rapid identification and deployment of effective treatments using drugs that are already well-understood (Johnson et al., 2021).

Traditional Methods of Drug Repurposing and Their Limitations

Traditional methods of drug repurposing typically involve a systematic approach where researchers explore existing drugs based on their known pharmacological profiles, historical usage, and off-label applications (Subramanian et al., 2020). Common strategies include drug-centric approaches that focus on expanding the use of a specific drug to a new indication, disease-centric approaches that identify relationships between diseases and existing treatments, and target-centric approaches that link known biological targets with existing drugs. Despite these methodologies, traditional drug repurposing faces several limitations (Quazi, 2022). One major challenge is the lack of comprehensive data on all potential uses of existing drugs, which can hinder the identification of promising candidates. Additionally, regulatory hurdles can complicate the process, as repurposed drugs may still require extensive clinical trials to demonstrate efficacy for new indications. This can lead to delays in bringing effective treatments to market and may discourage pharmaceutical companies from pursuing repurposing initiatives (Singh & Kaushik, 2023).

Potential Benefits:

The potential benefits of drug repurposing are substantial and include significant cost reduction, faster availability of therapies, and reduced risk compared to traditional drug development (Ahmed et al., 2023). Developing a new drug from scratch can take over a decade and cost billions of dollars; however, repurposed drugs can often be brought to market in a fraction of that time—typically within 3 to 12 years—at a cost that is 50% to 60% less than new drug development (Guedj et al., 2022). This efficiency is largely due to the established safety profiles of repurposed drugs, which allow researchers to bypass early-stage trials focused on safety and instead concentrate on demonstrating efficacy for new indications. Furthermore, with approximately 30% of repurposed drugs achieving market approval compared to only about 10% for new compounds, there is a compelling market-driven incentive for pharmaceutical companies to invest in this strategy. Overall, drug repurposing not only enhances the therapeutic landscape but also offers hope for patients suffering from diseases with limited treatment options by providing quicker access to potentially life-saving therapies (Tran, Wibowo, & Chong, 2023).

Role of Artificial Intelligence in Drug Repurposing

Artificial intelligence (AI) plays a transformative role in drug repurposing by enhancing the efficiency and effectiveness of the identification process for new therapeutic uses of existing drugs. One of the primary ways AI contributes is through data mining and analysis (Blanco-González et al., 2023). AI algorithms can sift through vast amounts of data derived from clinical trials, electronic health records, and scientific literature to uncover hidden relationships between drugs and diseases. This capability allows researchers to identify potential repurposing candidates that may not be immediately obvious through traditional methods (Leek et al., 2010). For instance, AI can analyze patterns in patient responses to medications, highlighting off-label uses or uncovering new indications based on historical data. By leveraging high-throughput multi-omics technologies and computational methods, AI facilitates a more comprehensive understanding of drug interactions and biological pathways, ultimately accelerating the repurposing process. In addition to data mining, predictive modeling and simulations are essential components of AI's role in drug repurposing. Machine

learning algorithms can predict which existing drugs might be effective against new diseases by analyzing their mechanisms of action and biological targets (Yersal, 2014). These models assess vast datasets to draw correlations between drug properties and disease characteristics, enabling researchers to prioritize candidates based on predicted efficacy. For example, AI-driven simulations can model how a drug would interact with specific biological pathways associated with a disease, providing insights into its potential therapeutic effects. This predictive capability not only streamlines the selection of promising repurposing candidates but also helps mitigate risks associated with clinical trials by forecasting patient responses and outcomes (Sorlie et al., 2001).

Techniques and Tools Used in AI-Driven Drug Repurposing

Machine learning (ML) is one of the most widely used approaches, where algorithms learn from historical data to make predictions about drug-disease interactions. ML can analyze complex datasets to identify patterns that suggest new therapeutic uses for existing drugs (Wang & Avillach, 2021).

Natural language processing (NLP) is another critical technique that allows researchers to extract valuable information from unstructured text data, such as research articles and clinical trial reports. By analyzing scientific literature, NLP can uncover previously overlooked connections between drugs and diseases, facilitating the identification of potential repurposing opportunities (Widen et al., 2021).

Deep learning (DL) is an advanced subset of machine learning that utilizes neural networks to model complex relationships within large datasets. DL techniques have shown great promise in drug discovery by enabling more accurate predictions regarding drug efficacy and safety profiles. For instance, deep learning models can analyze genomic data to identify how specific drugs might affect gene expression related to various diseases. Several AI platforms and systems are specifically designed for drug repurposing efforts (Pudjihartono et al., 2022).

One notable example is RepurposeDrugs, which utilizes machine learning algorithms to predict outcomes across different phases of clinical trials for repurposed drugs. This platform can estimate the likelihood of approval for specific indications based on historical trial data, helping prioritize clinical trial efforts (Abubaker Bagabir et al., 2022).

Another prominent system is TxGNN, a graph foundation model that employs graph neural networks to perform zero-shot drug repurposing across thousands of diseases, even those without existing treatments. These platforms exemplify how AI technologies are revolutionizing the field of drug repurposing by providing innovative solutions that enhance efficiency and effectiveness in identifying new therapeutic applications for established medications (Haug & Drazen, 2023).

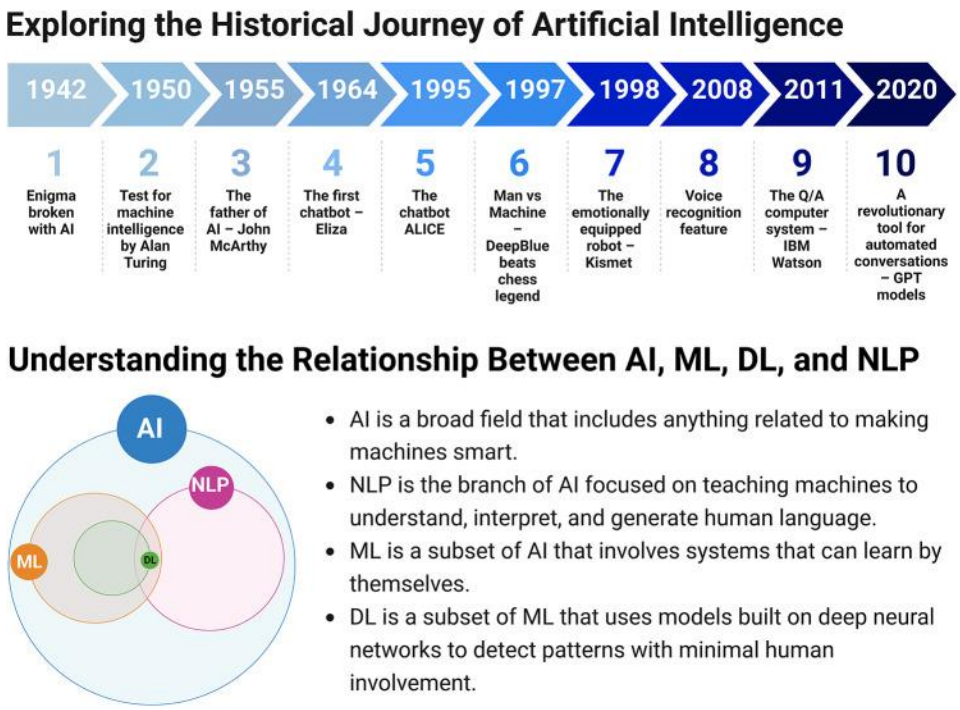

Fig. 1: Exploring the historical journey of AI

Tracing the Evolution of AI with a Better Understanding of the Relationship Between AI, ML, DL, and NLP (Hautz et al., 2019)

Applications of AI in Clinical Drug Repurposing

Artificial intelligence (AI) is increasingly being leveraged to identify treatments for rare and complex diseases, which often present unique challenges due to limited patient populations and scarce data (Gandhi & Sabik, 2014). Traditional drug discovery methods can be prohibitively lengthy and costly, particularly for conditions that lack extensive research or therapeutic options. However, AI offers innovative solutions by utilizing advanced data analytics to uncover potential repurposing candidates among existing drugs. For instance, AI algorithms can mine electronic health records (EHRs), genomic databases, and scientific literature to identify patterns and relationships that may suggest effective treatments for rare diseases.AI's ability to integrate diverse datasets is particularly beneficial in the context of rare diseases, where patient data can be heterogeneous and fragmented (Jiang et al., 2017). By employing machine learning techniques, researchers can analyze these datasets to identify previously overlooked drug-disease connections. For example, a study highlighted the use of machine learning models to evaluate existing medications for their potential efficacy against Pitt-Hopkins syndrome, a rare genetic disorder. Such applications demonstrate how AI can facilitate the identification of new therapeutic options for patients with rare conditions, ultimately improving treatment accessibility and outcomes (Matheny, Whicher, & Thadaney Israni, 2020). Moreover, AI-driven platforms are being developed specifically to address the needs of rare disease research. These platforms utilize algorithms that can process vast amounts of biomedical data to prioritize drug candidates for repurposing. By focusing on the

unique characteristics of rare diseases, AI technologies are paving the way for more targeted and effective treatment strategies that would be difficult to achieve through conventional methods (Berlyand et al., 2018).

AI in Oncology and Chronic Disease Management

In oncology and chronic disease management, AI is playing a pivotal role (Figure 2) in enhancing drug repurposing efforts by providing insights into existing therapies that may be effective against various cancers or long-term health conditions. The complexity of cancer biology, characterized by diverse genetic mutations and varying responses to treatment, necessitates innovative approaches for identifying effective therapies. AI algorithms can analyze large datasets from clinical trials, patient records, and molecular profiling studies to identify potential repurposing opportunities among approved drugs (Panch, Szolovits, & Atun, 2018). For example, AI has been employed to explore the repurposing of antidiabetic medications like metformin for cancer treatment. Research has shown that metformin may have anti-cancer properties through its effects on metabolic pathways involved in tumor growth. By utilizing machine learning techniques to analyze clinical data, researchers can assess the efficacy of such drugs across different cancer types and patient demographics, leading to more personalized treatment plans (Vandenberg et al., 2020). Additionally, AI tools are being used to optimize treatment regimens for chronic diseases such as diabetes, hypertension, and heart disease. By analyzing patient data in real-time, AI can help healthcare providers make informed decisions about medication adjustments or combinations that may enhance therapeutic outcomes. This capability is particularly valuable in managing chronic conditions where patients often require multiple medications tailored to their individual needs.AI's role in oncology and chronic disease management extends beyond identifying repurposed drugs; it also includes predicting patient responses to treatments based on genetic profiles and clinical histories (Smith & Kirby, 2020). This predictive modeling enables clinicians to select therapies with higher probabilities of success while minimizing adverse effects. AI is revolutionizing drug repurposing in oncology and chronic disease management by facilitating the discovery of new applications for existing medications and enhancing personalized treatment approaches (Go, Kim, Byeon, & Lee, 2018).

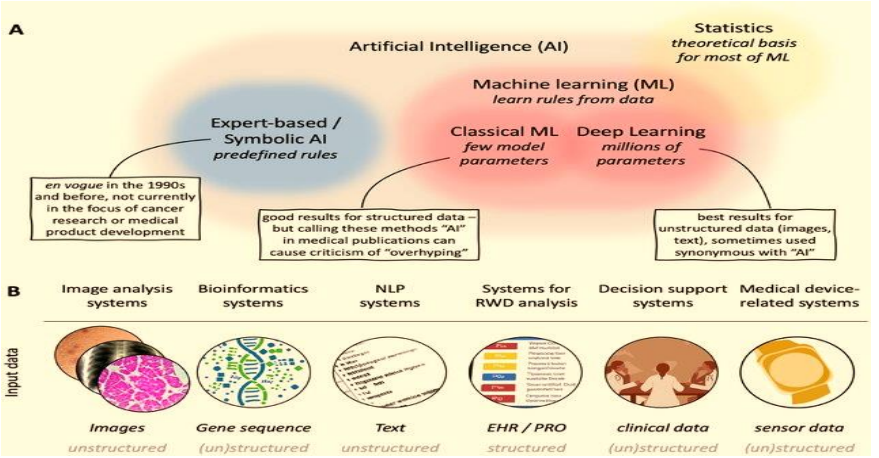

Fig. 2: Artificial intelligence in oncology

Challenges in AI-Driven Drug Repurposing

Data Quality and Availability Issues

One of the primary challenges in AI-driven drug repurposing is the quality and availability of data. Effective machine learning and artificial intelligence algorithms rely on large, high-quality datasets to generate accurate predictions and insights. However, many existing datasets may be incomplete, inconsistent, or lack standardization, which can significantly hinder the performance of AI models (Weis, Jutzeler, & Borgwardt, 2020). For instance, electronic health records (EHRs) may contain missing data or errors that can skew results, leading to incorrect conclusions about a drug's potential efficacy for a new indication. Additionally, the diversity of data sources—ranging from clinical trial results to genomic databases—can complicate integration efforts, making it difficult to create comprehensive datasets that reflect the full spectrum of patient experiences and drug interactions. Addressing these data quality issues is crucial for enhancing the reliability of AI-driven drug repurposing efforts and ensuring that the insights generated are actionable (Smith, Kang, & Kirby, 2018).

Ethical Concerns and Regulatory Hurdles

Ethical concerns and regulatory hurdles also pose significant challenges in the realm of AI-driven drug repurposing (Peiffer-Smadja et al., 2020). The use of AI in healthcare raises questions about patient privacy, informed consent, and data security, particularly when sensitive health information is involved. Ensuring that patient data is handled ethically and responsibly is paramount to maintaining public trust in AI technologies. Furthermore, the regulatory landscape for drug repurposing remains complex and often lacks clear guidelines tailored to AI methodologies. While repurposed drugs benefit from established safety profiles, they still require rigorous testing to demonstrate efficacy for new indications (Undru, Uday, & Lakshmi, 2022). The absence of standardized protocols for evaluating AI-driven repurposing candidates can lead to uncertainty among researchers and pharmaceutical companies regarding the approval process. Developing a cohesive regulatory framework that addresses these ethical considerations while facilitating innovation will be essential for advancing AI-driven drug repurposing (Mijwil & Aggarwal, 2022).

Integration into Clinical Workflows

Integrating AI-driven drug repurposing into existing clinical workflows presents another significant challenge (Becker et al., 2022). Healthcare providers often operate within established systems that may not readily accommodate new technologies or methodologies. For AI tools to be effective in clinical settings, they must be seamlessly integrated into everyday practices without disrupting patient care or overwhelming clinicians with complex data outputs (Raghunath et al., 2021). This requires not only user-friendly interfaces but also adequate training for healthcare professionals to understand and utilize AI insights effectively. Additionally, there must be a clear communication strategy that conveys the benefits of using AI in drug repurposing to all stakeholders involved in patient care. Overcoming these integration challenges is critical for ensuring that AI-derived insights translate into practical applications that enhance treatment options for patients (Alfaras, Soriano, & Ortín, 2019).

Overcoming Bias in AI Models

Overcoming bias in AI models is a crucial challenge that can significantly impact the success

of drug repurposing initiatives (Li, Zhao, & Zou, 2021). Bias can arise from various sources, including the datasets used to train models, which may not represent diverse populations adequately or may reflect historical disparities in healthcare access and treatment outcomes. If AI models are trained on biased data, they may produce skewed results that fail to account for variations in how different demographic groups respond to medications (Haenssle et al., 2018). This can lead to inequitable treatment recommendations and exacerbate existing health disparities. To mitigate bias, it is essential to ensure that training datasets are representative of the populations being studied and to implement techniques such as fairness-aware algorithms that actively address potential biases during model development. By prioritizing fairness and inclusivity in AI-driven drug repurposing efforts, researchers can enhance the reliability of their findings and promote equitable access to effective therapies across diverse patient populations (Han et al., 2020).

Future Prospects and Innovations

The future of drug repurposing will increasingly rely on the synergy between AI and other cutting-edge technologies, particularly genomics and proteomics (Kim et al., 2020). The integration of AI with genomic data enables researchers to identify genetic variations associated with disease susceptibility and treatment responses. By analyzing genomic profiles alongside clinical data, AI can help uncover novel biomarkers that indicate which patients are likely to benefit from specific therapies. This approach enhances personalized medicine by tailoring treatment plans based on individual genetic backgrounds. In proteomics, AI can assist in analyzing complex protein expression patterns and interactions that may reveal new therapeutic targets for existing drugs (McKinney et al., 2020). For instance, AI algorithms can predict protein-protein interactions or identify biomarkers indicative of disease states, facilitating the discovery of new applications for established medications. The combination of AI with multi-omics approaches—integrating genomics, proteomics, transcriptomics, and metabolomics—provides a comprehensive understanding of biological systems and disease mechanisms. This holistic view is crucial for identifying potential repurposing candidates that may have been overlooked in traditional research paradigms (Ahsan, Luna, & Siddique, 2022). AI's role in precision medicine is poised to expand significantly as researchers continue to explore its applications in drug repurposing (Myszczynska et al., 2020). Precision medicine aims to customize healthcare treatments based on individual patient characteristics, including genetic makeup, environmental factors, and lifestyle choices. AI technologies can analyze large datasets to identify patterns that inform treatment decisions tailored to specific patient profiles (Esteva et al., 2017). For example, AI-driven predictive modeling can help determine which existing drugs are most likely to be effective for particular patient subgroups based on their genomic data or disease characteristics. This capability not only enhances the efficacy of treatments but also minimizes adverse effects by ensuring that patients receive therapies aligned with their unique biological profiles. Furthermore, AI can assist in monitoring patient responses to treatments in real-time, allowing for timely adjustments to therapy as needed (Topol, 2019).

2. Conclusion

The transformative potential of artificial intelligence (AI) in drug repurposing is profound and

far-reaching. By harnessing the power of advanced algorithms and data analytics, AI is revolutionizing the way researchers identify new therapeutic uses for existing medications. This innovative approach not only accelerates the discovery process but also enhances the efficiency of clinical trials, ultimately leading to faster access to effective treatments for patients. The ability of AI to analyze vast datasets from clinical trials, electronic health records, and scientific literature allows for the identification of previously overlooked drug-disease relationships, paving the way for novel therapeutic applications. Additionally, the integration of AI with other technologies such as genomics and proteomics further enriches our understanding of complex biological systems, enabling more personalized and targeted treatment strategies. However, to fully realize the potential of AI in drug repurposing, there is an urgent need for interdisciplinary collaboration among AI researchers, clinicians, and policymakers. Such collaboration is essential to bridge the gap between technological innovation and clinical application. By working together, these stakeholders can ensure that AI-driven insights are effectively translated into practice, addressing real-world healthcare challenges. Policymakers must also play a crucial role in creating a supportive regulatory framework that fosters innovation while safeguarding patient safety and privacy. As we move forward into an era where AI continues to shape the future of medicine, it is imperative that we cultivate partnerships across disciplines to maximize the benefits of AI in drug repurposing and ultimately improve patient outcomes on a global scale.

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