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ARTIFICIAL INTELLIGENCE

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ABSTRACT: A subfield of computer science called artificial intelligence (AI) gives robots the ability to operate effectively and analyse complicated data. The amount of research on AI has grown significantly, and its application to healthcare services and research is progressing more quickly. The advantages and disadvantages of AI in medical and pharmaceutical research are discussed in detail in this article. In order to select the research and review articles published within the last five years, the literature was gathered from sources like PubMed, Science Direct, and Google Scholar using specific keywords and phrases like "Artificial intelligence," "Pharmaceutical research," "drug discovery," "clinical trial," and "disease diagnosis." This article provided a thorough analysis of the use of AI in illness diagnosis, digital therapy, personalised treatment, drug development, and pandemic or epidemic forecasting (1).

The application of artificial intelligence in pharmaceutical technology has grown over time, and it may help save time and money while also improving our understanding of the connections between various formulations and process factors (2).

The article discusses the development of novel peptides from natural foods, the treatment and management of rare diseases, drug adherence and dosage, and challenges to the adoption of AI in pharma(2).

KEYWORDS:
Drug, robotics, Digital, intelligence, treatment, therapy, diagnosis.

I. INTRODUCTION:

Artificial intelligence (AI) encompasses a range of intelligent processes and behaviours developed through computational models, algorithms, or rules. It enables machines to mimic human cognitive functions like learning and problem-solving. AI is making significant inroads in the healthcare sector, impacting clinical decision-making, disease diagnosis, and automation (3). It also holds great potential for pharmaceutical and healthcare research by leveraging its ability to analyse vast amounts of data from various sources (4,5,6).

AI technologies play a crucial role in healthcare, encompassing various applications such as machine learning (ML), natural language processing (NLP), physical robots, and robotic process automation (7). ML, including neural network models and deep learning, is utilized in the analysis of imaging data to identify important factors with clinical significance, particularly in the field of cancer diagnosis (8,9). NLP employs computational methods to comprehend human speech and extract meaningful information from unstructured data like doctors' notes and laboratory reports, facilitating more accurate diagnoses and informed treatment decisions (10).

AI-based solutions have paved the way for precise and rapid diagnoses, as well as customized treatment interventions. By analysing diverse data types such as symptoms, biometrics, imaging, and biomarkers, AI enhances the early detection of potential illnesses, increasing the likelihood of prevention (11,12). Physical robots find applications in nursing, telemedicine, cleaning, radiology, surgery, rehabilitation, and more. Robotic process automation automates repetitive administrative tasks in healthcare, such as prior authorizations, updating patient records, and billing (13).

The application of artificial intelligence in the pharmaceutical and biotechnology sectors has revolutionised how researchers create new medicines, treat diseases, and more during the last five years (14,15)

Differences between machine learning and artificial intelligence:

Machine learning (ML) is a field of artificial intelligence (AI) where the system learns from input data, predefined goals, and alternative actions to improve its performance through experience. Instead of relying on randomized parameters, ML operates on fixed values and aims to produce accurate results. It utilizes structured data formats for inputs and outputs, focusing on pattern recognition within large datasets and taking appropriate actions. ML does not involve decision-making but rather aims to generate mechanical solutions for enhanced machine performance. The program generating the algorithm efficiently integrates input and output.

On the other hand, AI is concerned with machines acquiring knowledge and skillfully applying it in real-life scenarios using real-time data. AI strives to mimic human-like behavior and execute specific tasks independently or in combination. It may involve multiple programming integrations, validations, and pattern recognition methods to achieve expected behavior. The primary objective of AI is to produce results through intelligent data evaluation, mining, and deep comprehension. It leverages dynamic parameters, smart real-time processing, and automation to simulate human intelligence and provide realistic solutions to complex problems. Unlike ML, AI does not rely on fixed algorithms but employs various levels and forms of analysis to seek optimal solutions. It encompasses the wisdom of learning, utilizing intelligence, and exercising discretion to differentiate right from wrong. AI involves computer learning with awareness of past iterations, alternative information processing, and cognitive analysis, demanding distinct capabilities (16).

This review discussed the role of artificial intelligence (AI) in the following areas.

- Disease diagnosis
- Digital therapy/personalized treatment:
  - Radiotherapy
  - Retina
  - Cancer
- AI in designing drug molecules
  - Predicting drug–protein interactions
  - Prediction of the target protein structure
- AI in advancing pharmaceutical product development
- AI in pharmaceutical manufacturing
- AI in quality control and quality assurance
- AI in clinical trial design
- AI In Robotics

Applications of AI in Pharmacy:

A. AI in Disease Diagnosis:

Disease analysis plays a crucial role in designing effective treatments and ensuring the well-being of patients. However, human inaccuracies and misinterpretations can hinder accurate diagnoses and create challenges. Artificial Intelligence (AI) has the potential to address these issues by enhancing accuracy and efficiency. Extensive research has explored various technologies and methodologies for disease diagnosis. As the human population evolves and environmental factors change, the demand for healthcare systems continues to increase (1,17). While some contradictory and non-analysing inconsistencies exist, new methods can be developed to fill the gaps in existing approaches. It is important to categorize patients based on the severity of their diseases, and AI can significantly contribute to the diagnostic process (18,19,20).

Diagnosis involves determining an individual's condition based on existing problems. Maintaining comprehensive health report forms for each patient helps gather information necessary for timely and accurate diagnoses (21). The analysis and interpretation of this information rely on the expertise of clinicians and may vary (22). Trust issues arise due to the availability of multiple diagnostic strategies, making it crucial to focus on AI for early disease prediction rather than just treatment or diagnosis. Early diagnosis facilitated by AI can lead to noticeable improvements in patient outcomes and enhance the efficiency of AI modules (23,24). Modern technology allows for the identification, extraction, and utilization of vast amounts of data using deep learning, neural networks, and algorithms (25,26,27,28,29). AI has gained significant importance in the diagnosis of major diseases such as cancer and dementia (30,31). Algorithms themselves are unbiased, but the data they are based on may introduce biases. To ensure statistical reliability, specific and relevant datasets are required (32,33,34). The acceptance of AI lies not in user input, but rather in the significance of identified patterns or clusters (35). Unsupervised learning can aid in the diagnosis of hepatitis.

Deep learning algorithms can adapt and improve predictions through evolutionary changes (36). While larger and diverse datasets are generally more suitable for AI, the complexity of outcomes can be challenging to comprehend. Deep learning has proven to be valuable in various diagnostic applications, such as the identification of dermatological conditions and the detection of atrial fibrillation (37). To estimate the performance of algorithms, cross-validation techniques, including random splitting into multiple sets, can be utilized. During evaluation, accuracy, sensitivity, and specificity are crucial metrics that receive significant attention in the field of artificial intelligence (38).

B. AI in Digital Therapy/Personalized Treatment:

AI possesses the capacity to derive significant connections from unprocessed data sets, thereby enabling their application in the detection, therapy, and control of diverse ailments. In the realm of medical science, a broad array of sophisticated methods is being utilized to computationally comprehend information, presenting possibilities for implementation across virtually every medical field. The complexities of clinical problems necessitate the acquisition, analysis, and application of vast amounts of knowledge (39). The progress of medical AI has facilitated healthcare professionals in tackling complex clinical dilemmas. Different frameworks such as Artificial Neural Networks (ANNs), evolutionary computational methods, fuzzy expert systems, and hybrid intelligent systems have become valuable tools for supporting healthcare workers in efficiently managing medical data.

ANNs are computational systems inspired by the biological nervous system. An artificial neural network (ANN) is composed of a series of computer processors, called neurons, that are interconnected to carry out parallel computations for data processing. The original artificial neuron was created using a binary threshold function (40). Among the various ANN models, the multilayer feed-forward perceptron is widely recognized and utilized. This type of network consists of several layers, including the input layer, one or more intermediate layers, and the output layer. Neurons within this network are interconnected through links with assigned numerical weights (41).

Paul Werbos introduced the novel technique known as "Backpropagation learning" in 1974, which encompasses a suitable learning algorithm (42). Artificial Neural Networks (ANNs) have found applications in diverse areas such as image analysis for diagnosis, data interpretation, and waveform analysis. Fuzzy logic is a specialized area of study that centres on the process of reasoning, cognition, and inference in order to identify and harness real-life phenomena. It operates by utilizing a graduated scale of membership values that span from 0 to 1, where 0 denotes falsehood and 1 signifies truth (43). Fuzzy controllers find practical applications in the management of vasodilators and anaesthetics within surgical settings.

An evolutionary computation technique, inspired by the natural process of evolution and survival of the fittest, has gained prominence. Genetic algorithms, in particular, are widely used(44). These algorithms generate multiple random solutions for a given problem and iteratively select the best solution while discarding inferior alternatives (45).

AI in Radiotherapy:

Automated treatment planning has emerged as an innovative technology with numerous benefits in the realm of radiotherapy treatment planning. It provides substantial enhancements in plan quality, consistency, and error reduction. The treatment workflow can be classified into three primary domains: the application of automated rules, the modelling of previous clinical knowledge for reasoning purposes, and the utilization of multi-criteria optimization techniques (46). Clinical guidelines can be implemented using a straightforward computer program that incorporates anatomical and physiological analysis of the patient, as well as mimicking the reasoning process typically employed in manual treatment planning. Spatial dose models and three-dimensional dose distribution have demonstrated considerable accuracy (47). Radiomics, utilizing various imaging biomarkers, can provide comprehensive information about tumours. Radiomics can be utilized to predict treatment outcomes and potential toxicity in individual patients undergoing radiation therapy (48).

AI in Retina:

The advancement of superior clarity retinal imaging has revolutionized the evaluation of human health. By capturing a single image of the retina, valuable personalized data can be extracted. Leveraging state-of-the-art medical technology, ophthalmologists and retinologists are able to develop individualized treatments and establish an ever-evolving learning healthcare system (49).

AI in Cancer:

AI has emerged as a valuable tool in the diagnosis and treatment of different types of cancers, including subtypes of non-Hodgkin lymphoma. In a research study that utilized gene expression data, a multilayer perceptron neural network demonstrated accurate predictions of lymphoma subtypes, such as mantle cell lymphoma (MCL), follicular lymphoma, diffuse large B-cell lymphoma (DLBCL), marginal zone lymphoma, and Burkitt lymphoma, with a high level of precision (50). Another analysis using artificial neural networks specifically focused on MCL and identified 58 genes that could predict survival outcomes with great accuracy. Among these genes, 10 were associated with poor survival, while 5 genes were linked to favourable survival outcomes(51).

In a study focusing on DLBCL, a combination of multilayer perceptron (MLP) and multivariate analysis was utilized to examine gene expressions. The results revealed four genes that exhibited a positive correlation with favourable survival outcomes, while three genes were found to be associated with poor survival (52). Likewise, in the context of follicular lymphoma (FL), the study employed MLP and radial basis function (RBF) neural networks to predict overall survival and prognosis. By analysing a comprehensive set of genes, the researchers identified 43 genes that were linked to overall survival prediction and 18 genes that were indicative of a poor prognosis (53).

To classify the cell-of-origin (COO) in DLBCL, researchers utilized deep learning techniques and genetic/transcribing information obtained through RNA-Seq in next-generation sequencing (NGS) platforms (54). This AI approach demonstrated reproducibility, efficiency, and cost-effectiveness, making it suitable for clinical applications.

AI has also been employed in cancer diagnosis to minimize time while ensuring high accuracy. PET imaging of lymphoma, based on AI algorithms, has been utilized for tumour burden evaluation. This technology has further facilitated tumour characterization, heterogeneity quantification, and prediction of treatment response (55).

Overall, these AI-based approaches have proven instrumental in predicting lymphoma subtypes, identifying prognostic markers, and facilitating accurate diagnosis and treatment planning for cancer patients (56,57).

C. AI in designing drug molecules:

I. Prediction of the target protein structure:

In the development of drug molecules, correctly identifying the target protein is crucial for effective treatment. Many proteins play a role in the progression of diseases, and in some cases, their expression levels are elevated. Therefore, to selectively target a disease, accurately predicting the structure of the target protein is essential for designing the drug molecule. Artificial intelligence (AI) can aid in structure-based drug discovery by predicting the three-dimensional (3D) structure of proteins. This prediction allows for the design of drugs that interact with the chemical Accurately predicting the structure of a target protein is crucial for the targeted treatment of diseases . In this regard, artificial intelligence (AI) plays a significant role in structure-based drug discovery by providing predictions of the three-dimensional (3D) structure of proteins. This predictive capability enables the design of drugs that interact effectively with the chemical environment of the target protein site. By leveraging AI techniques such as deep neural networks (DNNs), one notable tool in this field is Alpha Fold. Alpha Fold analyses the distances between neighbouring amino acids and the angles of peptide bonds to generate its predictions. Its impressive performance is evident from correctly predicting 25 protein structures out of a set of 43. This AI-driven approach allows for the anticipation of compound effects on the target protein and facilitates consideration of safety aspects before drug synthesis or production. environment of the target protein site, enabling the anticipation of compound effects on the target and consideration of safety before synthesis or production (58).

One prominent AI tool in this field is Alpha Fold, which utilizes deep neural networks (DNNs) to analyse the distances between adjacent amino acids and the corresponding angles of peptide bonds. By leveraging these techniques, Alpha Fold has demonstrated impressive results, correctly predicting 25 out of 43 protein structures.

Al Qurashi conducted a research study that explored the application of recurrent neural networks (RNN) in the field of protein structure prediction. The study proposed a novel approach called recurrent geometric network (RGN), which consisted of three distinct stages: computation, geometry, and assessment. In this approach, the RGN utilized encoded information from the primary protein sequence, along with torsional angles of a specific residue and an incomplete backbone derived from the preceding geometric unit. By processing this input, the RGN generated a new backbone as output, with the final unit producing the 3D structure as the ultimate prediction.

To assess the accuracy of the predicted protein structures, the study employed a metric called distance-based root mean square deviation (dRMSD). This metric allowed for a comparison between the predicted structures and experimental ones. The study aimed to optimize the parameters of the RGN in order to minimize the dRMSD between the predicted and experimental structures, thus enhancing the accuracy of the predictions.

Al Qurashi conducted a study that proposed an AI-based approach to predict protein structures faster than Alpha Fold. However, they acknowledged that Alpha Fold is expected to achieve higher accuracy when predicting structures of proteins that have similar sequences to reference structures.

In another research project, a MATLAB-based methodology was employed to predict the 2D structure of a protein. The study utilized a non-linear three-layered neural network toolbox with a supervised learning approach, employing a feed-forward architecture and backpropagation error algorithm. MATLAB was utilized to train the input and output datasets, and the neural networks were used as learning algorithms and performance evaluators. The reported accuracy achieved in predicting the 2D structure was 62.72% (58,59).

II. Predicting drug–protein interactions:

Accurate prediction of drug-protein interactions is crucial for the success of therapeutic interventions. It plays a significant role in understanding the effectiveness and efficacy of drugs, facilitating drug repurposing, and preventing polypharmacology. Artificial intelligence (AI) methods have demonstrated their value in precisely predicting the interactions between drugs and receptors or proteins, leading to improved therapeutic outcomes (58).

In a notable study conducted by Wang et al., a model was developed using the Support Vector Machine (SVM) approach. The researchers trained this model on a dataset of 15,000 protein-ligand interactions, incorporating both the primary protein sequences and structural characteristics of small molecules. This model yielded impressive results by uncovering nine previously unknown compounds and their interactions with four important targets(60).

Another study by Yu et al. utilized two Random Forest (RF) models to predict potential drug-protein interactions. These models integrated pharmacological and chemical data and were validated against established platforms like SVM. The RF models demonstrated remarkable sensitivity and specificity, allowing for the accurate prediction of associations between drugs and their targets. This methodology has the potential to be expanded to encompass associations between targets and diseases, as well as connections between different targets. As a result, this technique has the capacity to expedite the process of drug discovery(61).

In a different approach, Xiao et al. employed the Synthetic Minority Over-Sampling Technique and the Neighbourhood Cleaning Rule to optimize data for developing I Drug Target. I Drug Target is a composite predictor consisting of four sub predictors: I Drug-GPCR, I Drug-Chi, I Drug-Enz, and I Drug-NR. These sub-predictors detect the correlations between medications and various biological components such as G-protein-coupled receptors (GPCRs), ion channels, enzymes, and nuclear receptors (NR). Through target-jack-knife tests comparing I Drug Target with existing predictors, it demonstrated superior prediction accuracy and consistency.

Deep DTnet, a deep learning approach based on cellular networks, has been investigated for its potential in predicting the therapeutic applications of topotecan, a topoisomerase inhibitor. Additionally, it shows promise for treating multiple sclerosis by specifically inhibiting the ROR-gt (human retinoic acid receptor-related orphan receptor) receptor. A US provisional patent now provides protection for the platform.

Self-organizing maps (SOMs), which fall under the area of unsupervised machine learning, are used in the field of medication repurposing. For a certain collection of pharmacological compounds, they use a ligand-based strategy to find novel off-targets. The system is trained on a set of substances with known biological activity before being applied to the analysis of other substances.

In a recent study, a deep neural network (DNN) was utilized to repurpose existing drugs that have demonstrated activity against SARS-CoV, HIV, influenza virus, and act as 3C-like protease inhibitors. The AI platform was trained using extended connectivity fingerprints (ECFP), functional-class fingerprints (FCFPs), and the octanol-water partition coefficient (A

Log P _count). The study identified 13 drugs that exhibited promising cytotoxicity and viral inhibition profiles, warranting further development (62).

D. AI in advancing pharmaceutical product development:

AI has the potential to revolutionize the process of discovering and developing novel drug molecules. Traditionally, this process relied on a trial-and-error approach. However, AI can now replace this inefficient method by leveraging various computational tools and techniques.

In the field of formulation design, AI can help address key challenges such as stability issues, dissolution, and porosity using Quantitative Structure-Property Relationship (QSPR) models. These computational tools can analyse and predict the behaviour of drug molecules, assisting in the selection of suitable excipients and optimizing the dosage form's delivery characteristics.

To facilitate this process, decision-support tools based on rule-based systems have been developed. These tools consider the physicochemical attributes of the drug and recommend the appropriate type, nature, and quantity of excipients. They also incorporate a feedback mechanism to monitor the formulation development process and make intermittent modifications when necessary(63).

A notable example of AI integration in formulation development is the work by Guo et al. They combined Expert Systems (ES) and Artificial Neural Networks (ANN) to create a hybrid system for developing direct-filling hard gelatine capsules of piroxicam. The Model Expert System (MES) employed input parameters to make decisions and provide recommendations for formulation development. Meanwhile, the ANN utilized backpropagation learning to establish correlations between formulation parameters and the desired dissolution profile. The control module ensured smooth coordination between the MES and ANN, enabling hassle-free formulation development(64).

In summary, AI-driven approaches in formulation design offer promising solutions to overcome the limitations of traditional trial and error methods. By leveraging computational tools, rule-based systems, and hybrid systems, AI can significantly enhance the efficiency and effectiveness of developing dosage forms with desired delivery characteristics.

E. AI in pharmaceutical manufacturing:

With the increasing complexity of manufacturing processes and the growing demand for improved efficiency and product quality, modern manufacturing systems are undergoing continuous transformation through the integration of human knowledge into machines [88]. The utilization of artificial intelligence (AI) in the manufacturing sector holds great potential, particularly in the pharmaceutical industry. An illustrative instance involves the application of Computational Fluid Dynamics (CFD), which utilizes Reynolds-Averaged Navier-Stokes solvers technology to assess the influence of agitation and stress levels on different equipment, including stirred tanks. This automated approach to pharmaceutical operations significantly improves their effectiveness by increasing efficiency (65).

Other advanced systems like A combination of large eddy simulations and direct numerical simulations employ sophisticated methodologies to solve intricate flow problems encountered in manufacturing processes The development of the Champetre platform has made digital automation for the synthesis and production of molecules easier. This platform has been effective in enabling the synthesis and manufacture of compounds like sildenafil, diphenhydramine hydrochloride, and rufinamide with comparable yield and purity to manual synthesis thanks to the incorporation of chemical codes and the use of a scripting language called Chemical Assembly. Furthermore, AI technologies have demonstrated their efficacy in optimizing the granulation process in granulators of varying capacities (ranging from 25 to 600 litres) by estimating the completion time accurately. By utilizing technology and neuro-fuzzy logic, critical variables have been correlated with their corresponding responses. This correlation has allowed the derivation of polynomial equations to predict the proportion of granulation fluid required, optimal speed, and impeller diameter for both geometrically similar and dissimilar granulators.

In the pharmaceutical industry, Discrete Element Method (DEM) has found widespread application. DEM has been employed to study powder segregation in binary mixtures, investigate the effects of blade speed and shape, predict the possible path of tablets during the coating process, and analyse the time spent by tablets under the spray zone. Artificial Neural Networks (ANNs) and fuzzy models have also been utilized to study the relationship between equipment parameters and the

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likelihood of tablet capping on manufacturing lines, aiming to reduce this issue (66).

F. AI in quality control and quality assurance:

The manufacturing process of a product involves a careful balance of different parameters (67). To maintain quality control and ensure consistency between batches, manual intervention is often required. However, this approach may not always be optimal, highlighting the need for implementing artificial intelligence (AI) at this stage. As part of Current Good Manufacturing Practises (cGMP), the FDA has adopted a "Quality by Design" approach to better understand the crucial processes and precise standards that determine the ultimate quality of pharmaceutical goods.

In their research, Gams et al. combined the work of humans with AI. They examined initial production batch data and generated decision trees, which were subsequently converted into rules and examined by operators to direct subsequent production cycles. Goh et al. focused on studying the dissolution profile of theophylline pellets as an indicator of batch-to-batch consistency. They utilized an artificial neural network (ANN) to predict the dissolution of tested formulations, achieving an error rate of less than 8% (68).

AI can also be applied to regulate in-line manufacturing processes and achieve desired product standards [95]. For example, monitoring the freeze-drying process using an ANN-based system incorporates self-adaptive evolution, local search, and backpropagation algorithms. This enables the prediction of future temperature and desiccated-cake thickness under specific operating conditions, thereby ensuring quality control of the final product.

An automated data input platform, like a Digital Lab Notebook, can be used in conjunction with very advanced intelligent algorithms to improve quality assurance. In the Total Quality Management expert system, data mining and different knowledge discovery techniques can also be useful approaches for making complicated opinions as well as developing new technologies for intelligent quality management (69).

G. AI in clinical trial design:

Clinical trials are essential for evaluating the safety and effectiveness of a drug product in humans, focusing on specific diseases. However, these trials typically take 6-7 years to complete and require significant financial resources. Unfortunately, only one in ten molecules that enter clinical trials successfully receive clearance, resulting in substantial losses for the industry. These failures can be attributed to factors such as improper patient selection, insufficient technological prerequisite, and inadequate infrastructure. However, the abundance of digital medical data presents an opportunity to mitigate these failures through the implementation of AI (70).

Patient enrolment constitutes a significant portion of the clinical trial timeline. Ensuring the success of a clinical trial heavily relies on recruiting suitable patients, as failure to do so accounts for approximately 86% of cases. AI can play a crucial role in the selection process by employing patient-specific genome-exposome profile analysis. This approach aids in early identification of drug targets among the selected patient population, specifically during Phases II and III of clinical trials. Additionally, AI can be utilized to predict lead compounds and facilitate preclinical discovery before the initiation of clinical trials. Techniques such as predictive machine learning and other reasoning methods contribute to early identification of lead molecules that are likely to successfully navigate clinical trials while considering the targeted patient population (70).

30% of research investigations fail due to patient dropout, which forces further recruiting attempts to finish the experiment and wastes time and money. However, this problem may be solved by regularly monitoring participants and helping them follow the clinical trial's established procedure. For instance, during a Phase II study, Ai Cure created mobile software that efficiently tracked medicine consumption among patients with schizophrenia. The clinical trial's successful conclusion was eventually guaranteed by the technology's 25% boost in patient adherence rates (71).

H. AI In Robotics

Robotics and artificial intelligence have intertwined roots and a long history of scholarly discourse and interaction. While it can be argued that not all machines can be classified as robots, artificial intelligence also encompasses concerns related to virtual agents. Unlike artificial intelligence, robots are physical entities created as hardware. However, they are closely linked since the software agents controlling robots analyse data from sensors, make decisions, and direct actions in the real environment. The field of robotics has a wide range of applications (72). Additionally, as patients increasingly engage in their healthcare decisions, they may explore potential drug options. By

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employing target audience marketing strategies, pharmaceutical companies can ensure that accurate and timely information is provided to facilitate informed discussions between patients and healthcare providers (73).

IN PHARMA CHALLENGES TO ADOPT AI:

- Many pharmaceutical companies still perceive AI as a mysterious and unfamiliar technology due to its novelty and complex nature.
- Insufficient IT infrastructure poses a challenge as most existing applications and systems were not originally designed to accommodate artificial intelligence. Consequently, significant financial investments are required to upgrade the IT infrastructure of pharma firms.
- A significant portion of the data in the pharmaceutical industry is in free text format, necessitating extra effort to collect and transform it into a format suitable for analysis. Despite these limitations, AI is already reshaping the field of biotech and pharma.
- In the next decade, pharmaceutical companies will likely consider artificial intelligence as a commonplace and fundamental technology.

Future of Artificial Intelligence:

Companies like Google and Uber are already harnessing the power of AI to enable autonomous vehicles. AI technology will have a significant impact on the field of automated transportation, providing assistance to disabled drivers and enhancing safety to prevent accidents. Furthermore, advanced AI systems can support hazardous tasks in factory environments, potentially replacing human workers. AI systems equipped with data science and environmental technologies can also contribute to climate change predictions. It is estimated that approximately 80 percent of customer service operations will be efficiently handled by AI systems, ensuring effective and timely support. In the realm of personalized health management, AI systems demonstrate their capabilities in symptom identification and processing of medical data, simplifying the process for individuals. Additionally, cyborg technology can enhance the quality of life for patients by enabling communication with robotic systems, facilitating the use of artificial prosthetics. In space technology, AI can analyze orbital paths during launches and provide recommendations based on its observations. In the pharmaceutical industry, AI is poised to revolutionize the field by reducing costs, developing innovative treatments, and ultimately, saving lives. Therefore, biotech companies should seize the advantages offered by AI technology as soon as possible(74).

II. CONCLUSION:

The utilization of artificial intelligence (AI) in the healthcare industry encompasses a range of technologies that empower machines to perceive, comprehend, take action, and acquire knowledge for carrying out administrative and clinical healthcare tasks. Ultimately, the future lies in the collaboration between humans and machines, and as technology advances, clinical experts must adapt, learn, and progress. Rather than leading to the extinction of medical professionals, it signifies the evolution of medicine. AI and machine learning have numerous applications in the pharmaceutical field, such as disease identification and diagnosis, personalized treatment and behavioural modification, drug discovery and manufacturing, radiology and radiotherapy, smart electronic health records, prediction of epidemic outbreaks, sales and marketing, as well as predictive analytics, among others. Furthermore, AI and ML-based analytics prove to be particularly effective in advertising, as they excel in making ongoing complex decisions that require a high degree of judgment.

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