IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES
ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 1, Jan 2022

A Study on the Use of Machine Learning (ML) In Translational Medicine

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ABSTRACT: The vast progression of Internet web facilities, along with advances in computer technology and algorithm development, in addition to existing developments in high-throughput methodologies, facilitate the research establishment to obtain access to biological sets of data, medical evidence, and many database systems usually contain millions of pieces of scientific knowledge. Recent years have seen an explosion in the use of Artificial Intelligence (AI) and Machine Learning (ML) to make sense of massive amounts of data in the pharmaceutical industry, completely changing the face of research and innovation. . Author discusses the potential of ML to revolutionize the field of medicine by providing an overview of its applicability in drug research and development. The possibilities for applying ML methods to the field of Pharmacometrics are explored since they have the potential to radically alter the way model-informed drug discovery and development is conducted. Furthermore, the author suggests that cross-functional groups comprised of specialists in Clinical Pharmacology, Bioinformatics, or Biomarker Technology were necessary to fully utilize the potential of AI/ML-enabled Translational and Personalized Medicine.

KEYWORDS: Artificial Intelligence (AI), Drug Discovery, Machine Learning (ML), Patient, Translational Medicine.

1. INTRODUCTION

These days, Artificial Intelligence (AI) and its related subfields Machine Learning (ML) and Deep Learning (DL) are growing in popularity across many industries, such as the scientific ones (e.g., healthcare) due to their potential to revolutionize the domain and boost outcomes for patients across a wide range of medical specializations [1]. Health and clinical records on an individual basis may now be generated in real-time in a real-world setting, thanks to technological advances. They are fundamental to the technological transformation, patient participation in drug discovery, and healthcare democratization that offer the potential for advancing medical practice towards a more focused and individualized approach. The use of continuous forward, as well as reverse translation, focused on the patient has allowed pharmacological research and development to evolve into a very continuous interaction in recent times [2].

Numerous industries, from financial and banking markets to educational, distribution networks, manufacturing, retailing, and e-commerce, even healthcare, have benefited from the use of AI in a variety of forms and degrees. Artificial intelligence (AI) has been a key facilitator of many innovative commercial breakthroughs inside the technology sector. Computer scientists in the field of artificial intelligence (AI) aim to create intelligent computers that can carry out activities that would normally need a human brain. Automatic language translators, decision-making systems, speech-recognition interfaces, and more are all possible because of artificial intelligence. The study of AI encompasses several fields [3].

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Artificially intelligent technologies have come a long way in helping with patient diagnosis. Esteva et al.[4] employ clinical imaging data to construct classification models that assist clinicians in the detection of skin cancer, skin lesions, and psoriasis, respectively, in the area of visually oriented specialties like dermatology. To solve the binary classifier issue in learning algorithms, Esteva et al.[4] used 129,450 photos to train a deep convolutional neural network (DCNN) model to distinguish between two classes of skin lesions: keratinocyte carcinoma and seborrheic keratosis, as well as malignant melanoma or benign nevus. They also found that the DCNN was as accurate as a panel of 21 dermatologists with advanced training. Unlike dermatologists, who spend many years in medical college and depend on knowledge gained during diagnostic testing over years, AI systems may be trained to identify skin tumors with a competence level equivalent to dermatology in a short amount of time.

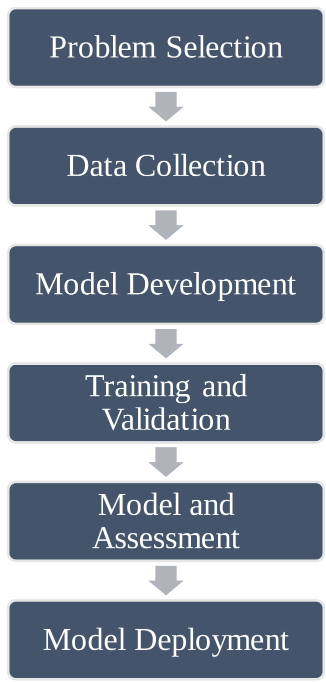

Figure 1: Image depicting the phases involved in creating an AI model.

The following structure is common in healthcare AI systems. To tackle a well-defined issue in the healthcare system, this kind of system begins with a vast quantity of data, then uses machine-learning algorithms to collect insight from that data, and then uses that information to provide a meaningful output. A typical AI solution's process is shown in Figure 1. Bot assistants who interpret language, transcribe documents, and organize photographs and information are just a few examples of the ways AI is being used in the healthcare profession[5].

2. DISCUSSION

There is significant evidence that our capacity to increase the utilization of data has been positively impacted by the incorporation and usage of AI/ML approaches throughout the translational to clinical drug development spectrum. The improvement of research and development (R&D) across 3 important inter-dependent core priorities that comprise the procedure of Translational Medicine

ISSN PRINT 2319 1775 Online 2320 7876

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i.e, target, patient, and dose has been made possible due to the improved organizational learning of the researched drug and also the disease/patient demography [6]. These tenets provide the foundation upon which novel exploratory medicines might create a collection of scientific evidence to demonstrate their efficacy in human clinical trials. To maximize the chances of success in clinical development and, ultimately, to be available to ensure product enrollment, trying to label, and guidelines for medicinal use at the right dose and in the context of relevant targeted therapies techniques in concert with diagnostic techniques where appropriate, to achieve the maximum benefit/risk across populaces and diagnostic and therapeutic contextual factors of use, reliable and effective data-driven enhancement alongside such three main pillars is essential [6].

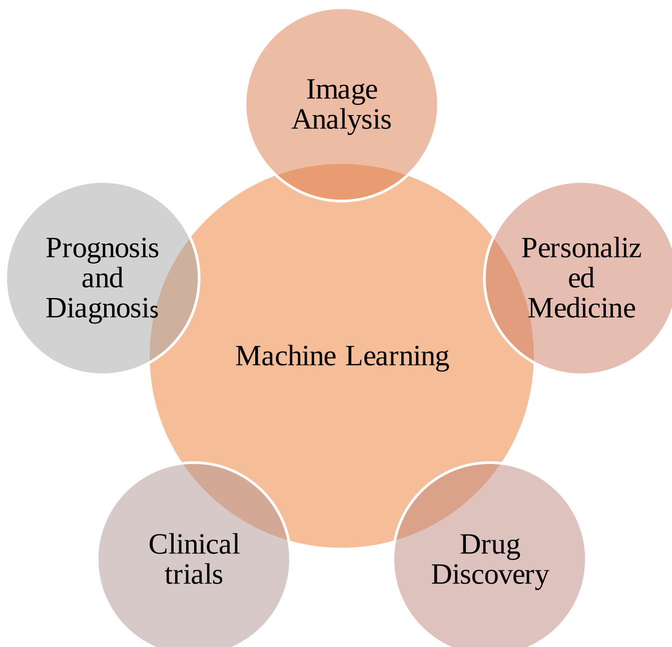

Figure 2: Illustration showing a simplified model of ML's role in translational medicine.

Therefore, these cutting-edge technologies are primarily intended to evaluate massive data using computer-based algorithms to extract useful information for bolstering decision-making [7]. Therefore, scientists may manage and execute a wide variety of jobs, such as diagnostic generation and suitable treatment selection, risk assessment and sickness categorization, medical error decrease, and productivity improvement, via the use of AI approaches. . In particular, a variety of high-throughput tests create data from a large number of patient samples, which is then collected into datasets that are in a machine-readable version, and presumably significant factors are located utilizing an ML-based algorithm. The algorithms can theoretically perform sophisticated tasks, such as classifying patients or forecasting their results, as it learns the interrelationships between the variables. Figure 2 provides a concise overview of ML's place in healthcare today [8].

Most artificial intelligence (AI) systems nowadays use machine learning to accomplish their goals (artificial intelligence). Its primary concern is the creation of computational systems and the analysis of massive data sets in search of meaningful patterns that might inform prudent action. With the help of machine learning, it is possible to learn automatically via systems and to improve

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based on one's experience without having to explicitly implement such a change. Algorithms, or sets of commands for a computer to carry out a certain job, provide the basis of its practical applications. The primary goal of machine learning techniques is to enable autonomous computer learning from data. The efficiency of algorithms increases over time with no further coding [9]. This study reviewed the use of machine learning (ML) in drug discovery and development through the lens of the three strategic foundations of Translational Medicine (target, patient, dosage), and provides insight into how these applications may revolutionize the field.

2.1.Target:

Finding the most effective medical target for a given illness is the primary goal of the "target" strategy pillar. To begin drug development aimed at regulating this target and, by extension, the illness, assurance in the biological target and treatment hypothesis must be established. There is a lot of data involved in this procedure, which is why it goes by a few different names. It employs a large battery of experiments and several datasets, all of which may help in the selection of new targets and the demonstration of their link to a disease. Several machine learning (ML) applications have evolved that make use of computational drug ability prediction algorithms for prioritizing target selection by narrowing the possible universe of drug-able targets and for clarifying the target-disease causation. Recent developments in natural language processing (NLP) have enabled effective and efficient access to accessible and unstructured resources, therefore unlocking knowledge and data on target and target-disease connection existent in reported literature [10]. Furthermore, these strategies may be used to identify the molecular foundation of drug-related hazards caused by off-target interactions, which can then be used to generate hypotheses for next-generation ("best-in-class") drug design to optimize therapeutic efficacy.

2.2.Patient:

The "patient" pillar emphasizes how crucial it is to choose the proper patient group for the experimental medicine and to determine whether a companion diagnostic test would be useful. Finding the appropriate patient population for the chosen illness is the objective. Although many successful precision therapeutics have been chosen with the right patient population in mind thanks to changes in specific genes (e.g., mutations in the epidermal growth factor receptor in non-small cell lung cancer influencing the choice of a suitable targeted therapies kinase inhibitor), the difficulties in precision medicine today are much more complicated because it is now possible to examine the effects of widespread pharmacogenetic variability on treatment response.

Importantly, those very techniques provide the chance to incorporate and evaluate the forecasting ability of large sets of longitudinal variables on the regarded results, while also allowing of that kind connections among patients' response, or late clinical endpoint, as well as patients' baseline factors (such as demographic trends, diagnostic, hereditary, research lab, and image analysis data). The findings from these kinds of studies may be incorporated into cutting-edge disease modeling and model-informed drug discovery and development (MID3) processes. Examples of such techniques include radionics, which involves the extraction and mining of various medical potentials to improve the quality to accurately measure tumor phenotypic traits, as well as robust ML methodologies (e.g., adopting RF) that are intended to identify accurate measurement radionics markers of disease prediction model of responding [11].

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2.3.Dose:

The "dose" pillar of Translational Medicine is concerned with the determination of the optimum dosage and dosing regimen for medicine through the most suitable administration route and/or drug delivery technology, taking into account the needs of a wide range of patient demographics and clinical settings. The goal is to find a safe and effective chemical that will have the intended effect on the target during the allotted time frame. This means expanding the treatment scope to include a broader range of clinical settings and subpopulations, rather than just the vast majority of patients [12]. It is important to develop exposure-response connections for both effectiveness and safety to properly guide the treatment efficacy. Understanding is aided greatly by MID3 methods. Longitudinal models of illness endpoints (such as tumor growth dynamics, and disease status scales), and also time to occurrence models of clinical studies, are used in these methods. In addition to identifying prognostic and predictive markers, such studies also evaluate the variance of therapeutic response to the potential medicine. To decrease model complexity and computing costs, this stage has traditionally been restricted to fixed and small types of factors. The impact of weight and/or age on the PK of dapsone was only detectable by Hall et al. using the multivariate adaptive regression splines ML technique because it occurs only within specified ranges of patient variables, bounded by various zones of discontinuity [13].

2.4.Prediction of drug targets and identification of biomarkers:

ML techniques to find viable drug candidates, as well as AI technologies, are developing with surprising effectiveness in drug target prediction. In the realm of neurodegenerative illnesses, for example, the authors asserted one of the most important advances in ML techniques used for therapeutic target selection in the drug discovery/drug repositioning sector. Indeed, deepDTnet, a computerized system based on the DL technique, was effectively applied in a repurposed strategy, offering intriguing indications for treating multiple sclerosis. An external testing set of therapeutically relevant pharmacological targets was used to verify the technique (277 targets). Evaluation findings revealed significant accuracy, with an area beneath the ROC curve of 0.89. The scientists confirmed their forecasts additionally to use an independent collection of clinical pharmacological targets, achieving a high accuracy of 0.89 measured by an area under the ROC curve. The results of this study presented new prospective therapeutic targets for the development of novel anticancer medicines [14].

With the increasing availability of high-quality cell images acquired, there are now relevant opportunities to apply ML-based algorithms to assist investigators in cell image analysis. In reality, the visual characteristics that are thought to be critical in creating predictions or diagnoses may be analyzed in general utilizing ML algorithms. These latter provide predictive, descriptive, and prescriptive evaluation capabilities to get important information that would otherwise be hard to obtain by human analysis, resulting in correct medical diagnoses. As a result, different clinical studies in recent years have permitted the application of AI in a variety of domains, including general pathological categorization, risk assessment, diagnostics, prediction, and prognosis of suitable treatment and likely reactions to a particular therapeutic intervention [15].

3. CONCLUSION

In recent years, AI and ML have developed as potent methods for extracting value from large datasets. The phenomenal growth in the application of AI and ML approaches across almost all sectors of technology, research, and medicine suggests that these methods will play a far larger role in the development of new treatments in the coming years. In many cases, AI applications have effectively addressed issues with results equivalent to those of human physicians, and the medical domain has given a fertile environment for AI researchers to evaluate their methodologies. Artificial intelligence (AI) solutions would be searched out as the cost of providing healthcare rises, with stakeholders looking for alternatives to costly components of patient care. A paradigm that includes both technical breakthroughs and human care must be explored, however, since cold technology cannot completely replace the individual components in patient care.

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