MEDICAL APPLICATIONS OF MACHINE LEARNING AND AI: A NEED OR AN OPPORTUNITY?

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ABSTRACT

Estimates put the amount of new healthcare data at 2,314,000 gigabytes in 2022, according to the global trend towards digitising health care systems. Better reasoning and more effective utilisation of obtained data are continuous goals of intelligent system development. This application is not limited to diagnostic purposes, which are retrospection-based. Prospective interpretation, which provides early prognosis, is another possible extension of this. However, these technologies leave doctors in a difficult position, caught between thorough scientific assessments and clinical case presentations. What they don't have is a solid foundation to go into when it comes to medical machine learning. With any luck, this paper will serve as a helpful resource for doctors who are curious in the applications of AI and ML in healthcare, particularly in the recent past. First, we will go over the broad strokes of history when it comes to healthcare systems' use of AI and ML concepts. Next, we provide a rundown of some of the medical specialties that are making use of or testing these technologies, including haematology, neurology, cardiology, oncology, radiology, ophthalmology, gene therapy, and cell biology.

KEYWORDS: Artificial Intelligence; Machine Learning; Medical Applications

INTRODUCTION

The integration of information technology in healthcare has enhanced several facets, ranging from the digitisation of patient data in electronic health records (EHR) to facilitating clinical decision-making. Due to the global trend of digitalising healthcare systems, the healthcare data generated in 2011 was estimated at 150 Exabytes (150 * 10^18), whereas the data created in 2020 is projected to reach 2314 Exabytes. Nevertheless, efficiently processing this data to extract valuable information and new knowledge continues to pose a significant problem. The continuously growing volume of acquired data exceeds the capacity of existing data analysis technologies. Consequently, healthcare systems are growing encumbered. This phenomenon is referred to as the "Data Rich/Information Poor (DRIP)" syndrome [1-6]. DRIP signifies that we are accumulating more data than we are capable of analysing. Fortunately, recent improvements in data analysis and decision-making systems render overcoming this obstacle achievable.

Medical data that has been collected can be analysed using various methods and at several levels. The initial stage involves obtaining individual patient data, wherein traditional alarm systems can assist in drawing attention to values that deviate from the usual range, as exemplified by cardiac electrocardiography (ECG) monitors. At the secondary level, various data sources are aggregated, integrated, and processed to yield results that can serve as input for another system that generates recommended differential diagnoses and conclusions based on a predefined set of rules. By adopting a tree-like hierarchy with the given data, these systems can facilitate the attainment of a credible explanation for the recorded symptoms. These rule-based systems are referred to as "Expert Systems." Expert Systems acquire knowledge via experience to replicate the decision-making capabilities of human specialists. These systems often answer to enquiries starting with "What" rather than "How," while concurrently elucidating the rationale for their decisions. A crucial characteristic of these systems is their ability to assimilate new experiences, therefore augmenting and refining their knowledge base. This subsequently enhances their decision-making capabilities. An initial instance of such systems is the "MYCIN" system [7-19].

These systems utilise a data transformation process that facilitates diagnosis and conclusions based on the established "data-information-knowledge-wisdom" model [8] (see Fig. 1). The continual advancement of intelligent systems seeks to improve reasoning and optimise the use of gathered data. The aim is to allow decision systems to operate prospectively and deliver early prognoses, in contrast to the retrospective method that just offers diagnoses and conclusions. Although these technological accomplishments are thoroughly documented [9], a concise lesson for clinicians aiming to comprehend the current status of this technology and its prospective applications is crucial. This state-of-the-art review provides clinicians with insights on the application of Artificial Intelligence (AI) in medicine. This study provides accessible insights on AI-Medicine interactions, aiming to foster a healthy dialogue on bridging the divide between the two fields, without attempting a comprehensive analysis of all medical AI applications.

Consequently, we will endeavour to elucidate fundamental terminologies and provide a concise discourse on the overarching trends in the use of machine learning and artificial intelligence ideas inside healthcare systems. Subsequently, we will enumerate several domains and instances where these technologies have been tested or implemented [20-27].

FUNDAMENTAL DEFINITIONS

Intelligence is one of the concepts that resists definitive definition. Effortless online browsing can provide several meanings that differ based on various viewpoints (philosophy, biology, psychology, mathematics, computer science). For the sake of this state-of-the-art review, Endeavour to gather several definitions identified in the literature. Intelligence is the capacity to formulate coherent designs, resolve issues, or produce commodities that are esteemed within a certain culture or professional domain. It employs association, memorisation, reasoning, comprehension, abstraction, conceptualisation, approximation, systematisation, and logical inference. These aspects are utilised to extract new information from established facts [10–12].

Artificial Intelligence denotes a system's capacity to accurately read external data, learn from it, and use that knowledge to accomplish specified objectives and tasks using adaptable methods. The primary element of AI is Machine Learning (ML), as seen in Fig. 2. Machine learning refers to the utilisation of computers to implement

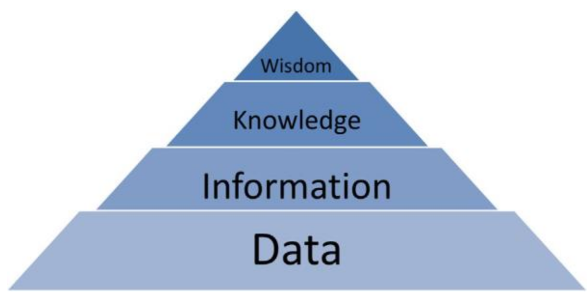

Fig. 1. Representing the classical pyramid of (date-information-knowledge wisdom).

Statistical models applied to data. It is a sub-discipline of artificial intelligence in which algorithms understand the correlations between input and output data. Three categories of machine learning algorithms may be identified: Supervised Learning, Unsupervised Learning, and Reinforcement Learning. In Supervised Learning, algorithms acquire connections by examining data samples delineated by a supervisor, often a human expert, in a process referred to as Training. Upon the acquisition of associations, they may be employed to forecast future instances in a process termed Testing [14].

In Unsupervised Learning, algorithms identify relationships within the data independently of external definitions. It is frequently employed for clustering, specifically to identify latent correlations in the input data, so creating subgroups that have shared characteristics. In Reinforcement Learning, the system acquires behaviour by a scalar reward or punishment signal. Punishment may be seen as a negative reinforcement signal that strengthens a behaviour aimed at evading its imposition [15]. It is noteworthy that a specific domain of machine learning, known as Deep Learning (DL), is frequently employed for analysing extensive data sets. Deep learning is a neural-based computing system that identifies connections within data using evolutionary experiments to minimise a cost function. Deep learning starts with arbitrary values (starting states) until it attains the optimal weights that most effectively minimise a specified cost function. The system continuously generates predictions and modifies its predictive methodology based on the incoming data [16].

Deep learning is an effective instrument for addressing intricate cognitive challenges [17,18]. Nevertheless, data challenges include insufficient volume, elevated sparsity, and subpar quality might constrain the effectiveness of deep learning techniques [19–24]. Ultimately, it is important to highlight that the use of machine learning extends beyond decision-making systems and encompasses many medical applications, including nanobots—minute robots utilised for specialised activities such as medicine delivery—and help for impaired patients. These applications, however intriguing, are beyond the purview of this study.

In the subsequent part, following a brief introduction to the patient data acquisition method, we will examine the medical disciplines in which AI technologies are now implemented: Patient Intake: Radiology, Haematology, Neurology, Oncology, Cell Biology and Cell Therapy, Cardiology, Ophthalmology.

Patient Intake: acquiring preliminary patient information the clinical process encompasses steps undertaken by healthcare professionals to evaluate and enhance a patient's health, commencing with an initial point (such as an appointment or emergency visit), followed by procedures, and culminating in an anticipated clinical outcome. Typically, the procedure starts with the retrieval and acquisition of the anamneses, also known as the case history. This entails a predetermined series of enquiries that the healthcare practitioner must pose throughout the patient consultation. This step has been partially digitised since the 1960s [26]. The digitisation mostly encompassed data storage and retrieval. Nonetheless, data gathering remains the responsibility of residents or nurses, as reliance on an automated system for this task is challenging. A person can translate the patient's informal narrative into a structured list of distinct probable causes, symptoms (along with their chronological progression), medical history, and additional pertinent comments. For example, if a patient states, “I believe I have diabetes,” a human physician would recognise that this is only the patient’s viewpoint, which would not be medically classified as “diabetes mellitus” until a comprehensive account of symptoms and diagnostic testing corroborates it. Envision, however, if the sufferer were to enter these information into a computer system. How will the system analyse this input?

Despite significant breakthroughs in natural language processing, no system has yet been able to extract medical terminology directly from patient input. Upon the collection of data, the Clinical Text Analysis and Knowledge Extraction System [27-41] can be employed to derive valuable insights from unstructured electronic health records. This organised information may then be utilised in several ways to enhance the case or even provide predictive modelling about the patient's future based on existing medical health data [24,28]. Upon entering the patient's details, healthcare practitioners may proceed with the medical examination. Results from medical examinations may need the implementation of laboratory testing or medical imaging, areas in which machine learning techniques might support the practitioner. In the subsequent paragraphs, we elucidate the applications of AI and ML in several medical domains.

RADIOLOGY

Regardless of whether the medical imaging conducted was Computerised Tomography (CT) or Magnetic Resonance Imaging (MRI), artificial intelligence approaches can aid the physician in deriving valuable insights from the images. Typically, a physician inputs the medical picture into the system, which then extracts its properties.

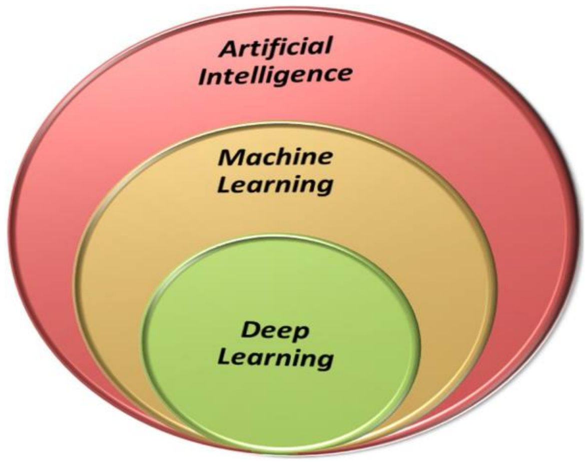

Fig. 2. Representing the inclusive relations between artificial intelligence, machine learning and deep learning.

visual representation. A forecast regarding the picture may be produced based on the values of these characteristics (also known as features). These forecasts may manifest in the following formats [29]:

● Segmentation: delineating boundaries around the components inside the picture.

● Labeling: recognising the components inside the picture.

● Detection and diagnosis: identifying a particular illness and forecasting its progression assist in producing the final radiology report.

Wu and colleagues [30] recently introduced an approach utilising logistic regression to diagnose triple-negative (TN) breast cancer in ultrasound pictures, achieving a sensitivity of 86.96% and a specificity of 82.91%.

A recent study employed deep learning to determine which X-ray pictures signify a healthy chest [31]. In this instance, while the experience of health specialists remains essential, the use of this approach would detect 50% of healthy chest cases, hence decreasing the number of instances requiring specialised classification. Computerised Tomography (CT) pictures may also be categorised with deep learning methodologies. [32] employed a machine learning-based method to differentiate between malignant and benign lung nodules by analysing characteristics in CT images of the parenchyma around the nodules. The claimed sensitivity was 100% and the specificity was 96%. [19] developed a machine learning algorithm to predict the grade of Glioblastoma utilising MRI scans. They attained an accuracy of 92%.

HAEMATOLOGY

The significant implementation of AI in haematology is quite recent. Cell diagnostic identification is among the most rapidly advancing fields. Three significant efforts in this domain have produced three exceptional application systems for flow cytometry immunophenotyping, bone marrow analysis, and peripheral blood analysis. The three platforms interconnect and correlate medical histories with laboratory findings stored in databases. Upon assessing 100 leukaemia patients, the three methods concurred on the final diagnosis in 94 instances and, with the physician's interpretation, in 99 instances [33–35].

Recent evaluations of machine learning techniques were conducted for diagnosing isolated haematological illnesses based solely on laboratory results. Two methodologies were employed: one utilised all available blood tests, while the other relied solely on a restricted set commonly assessed during patient intake. The respective prediction accuracies achieved were 88% and 86% for the five most probable diseases, and 59% and 57% for the single most probable disease [36].

Machine learning to assess a Japanese cohort of 26,695 patients for predicting the risk of acute graft versus host disease (aGVHD). The alternating decision tree (ADTree) machine learning technique was utilised to construct models from the training cohort, resulting in the selection of 15 criteria for the final model. The report indicates that aGVHD prediction scores also illustrated the correlation between the risk of GVHD and overall survival following HSCT. The algorithms generated clinically valid and resilient risk stratification ratings [37]. Another domain was the application of neural networks for peripheral blood analysis, highlighting two notable methodologies. The initial topic is to the diagnosis of haemoglobin disorders by laser cytometry utilising integrated isovolumetric sphering.

The approach demonstrated accuracy in nearly all instances of HbE, HbE linked with beta-thalassemia trait, iron deficiency anaemia connected with beta-thalassemia trait, and iron deficiency anaemia related to alpha-thalassemia [38,39].

The second is an AI model utilising cytometry, which assesses light to evaluate white blood cell volume and peroxidase activity in the perox channel, as well as nuclear density in the baso channel, to distinguish acute myeloblastic leukaemia samples according to FAB classification. This approach achieved a diagnosis effectiveness of 91% when evaluated on diseased samples [40].

A notable application is a data-mining algorithm that improves the diagnosis of Polycythaemia Vera (PV) utilising eight factors from the PV Study Group (PVSG) criteria, in addition to gender and haematocrit value (Hct). This method has undergone testing, revealing no substantial discrepancies between the model's diagnostic classification findings and the PVSG diagnostic criteria (98.1%). Moreover, the approach exhibited an identical accuracy rate utilising just four parameters: Haematocrit, Platelet count, Spleen, and WBC [41-59].

The European Group for Blood and Marrow Transplantation (EBMT) performed a data-mining analysis using a cohort of 28,236 patients in the same domain. This study employed a model utilising ten chosen factors to assess and predict overall mortality at 100 days post-allo-HSCT. This model demonstrated superior efficiency for this purpose compared to the EBMT score (area under the receiver operating characteristic curve of 0.701 versus 0.646; P < .001) [42].

A study conducted by the EBMT involving a cohort of acute leukaemia patients revealed that only a limited number of variables, including conditioning regimen, donor type, and disease stage, significantly influence treatment-related mortality, indicating that advancements in this field will likely necessitate further input.

Ultimately, gene profiling appears to be a valuable domain for the classification of certain illnesses. The integration of AI models with the DNA microarray technique has facilitated the establishment of novel disease classifications and the analysis of stem cells using both unsupervised and supervised learning methodologies. Unsupervised learning has been employed in class discovery, exemplified by the classification of multiple myeloma into five subgroups based on translocation oncogene and cyclin expression [44]. Supervised learning has been employed for class prediction, exemplified by acute myeloblastic leukaemia. The subsequent strategy is likely to be utilised to facilitate the differentiation of stem cells into particular lineages using fundamental genomic profiling [45].

NEUROSCIENCE

Electroencephalography (EEG) data serve as a valuable diagnostic instrument in neurology, offering insights into the brain's electrical activity. Numerous machine learning algorithms have been employed to analyse these data and provide predictions. [46] introduced an algorithm for detecting epileptic seizures in EEG records utilising two machine learning methodologies: Support Vector Machines (SVMs) and Genetic Algorithms (GAs), achieving an accuracy of 99.38% on the used EEG dataset. In a recent paper, [47] introduced an alternative machine learning approach known as Convolutional Neural Networks (CNNs), capable of detecting seizures with an accuracy of 93.3% utilising just two channels. To illustrate the many ways in which machine learning techniques have been aiding neurologists, we shall examine the instance of Parkinson's disease (PD). A recent study by [48] introduced a machine learning system capable of effectively predicting Parkinson's disease, with an accuracy of 96.40% from the early prognostic stage. The approach incorporates non-motor characteristics and olfactory impairment alongside Cerebrospinal Fluid (CSF) analyses and data from dopaminergic imaging biomarkers. Following the diagnosis of the condition, an additional machine learning system can be employed to forecast disease development. [49] used blood cytokines from a single time point (baseline) to forecast outcomes across a two-year period, one year subsequent to the first measurement.

ONCOLOGY

The application of AI and ML in combating cancer has mostly been seen as a promising strategy amongst the development of small chemical inhibitors, gene therapy, and modified biotherapies. These approaches are presently employed in radiation oncology for picture segmentation and radiotherapy dosage optimisation, where AI and ML have sufficiently fulfilled traditional norms and demonstrated more efficiency than manual planning in the majority of cases [50].

The creation of nanobots exemplifies a tangible use of artificial intelligence in cancer. Nanobots are utilised for addressing: 1) the issue of hypopermeation and insufficient diffusion of target therapeutic compounds at the application site; 2) targeting tumours that are deficient in vascularity yet exhibit active proliferation [51].

In patients having gastrectomy, a particular machine learning method has demonstrated superiority in individualising and refining risk-based categorisation for survival predictions [52].

A Google Research deep learning pathology program has been developed to detect the dissemination of breast cancer to adjacent lymph nodes using imaging data. This system achieved a localisation score of 89% compared to a 73% accuracy rate for pathologists [53].

Convolutional Neural Networks (CNNs) represent the predominant kind of supervised learning; their utilisation has been investigated in the assessment and monitoring of brain tumours, gliomas, and liver tumours in both 2D and 3D imaging, yielding notable accuracy outcomes in several trials relative to semi-automated RECIST-based methodologies [54–56].

CELLULAR BIOLOGY AND CELLULAR THERAPY

Cell biology and cell treatment encompass several cell kinds, along with various image screening and analysis methodologies. Therefore, it was imperative to employ machine learning to ascertain the optimal combinations of image screening and analysis techniques with cell types to distinguish across cell lines. Consequently, several breakthroughs have been achieved in this domain. For example, several commercially available ML automated microscopes can analyse over 100,000 cell pictures daily. Bioimaging technology can proficiently execute particular image analysis tasks, including object recognition, motion analysis, and morphometric feature measures.

Machine learning use experience rather than manual parameter adjustments to recognise cells and objects. It is more effective than traditional processing tools for executing difficult multi-dimensional data analysis tasks [59–61].

A crucial objective of machine learning in cell biology is to ascertain if an experimental perturbation, such as genetic mutation, results in a certain cellular phenotype, as detected by fluorescence. A machine learning system was recently assessed using actin-labeled fluorescence microscopy pictures from one normal human breast epithelial cell line and two human breast cancer cell lines exhibiting varying degrees of aggressiveness. The study demonstrated that the approach outperformed a human expert in the cell categorisation test [62-78].

This technology can be utilised to develop and improve novel production and quality control techniques for cell therapies, including chimeric antigen receptor T (CAR-T) cells, which have demonstrated clinically relevant characteristics such as glycolysis status, early memory phenotype, and minimal exhaustion profile.

Machine learning may also be applied to stem cell treatment, a method recently evaluated that shown significant variety in cell identities resulting from natural changes in regulatory dynamics. This strategy demonstrated more efficacy in comprehension. Cellular biology at the individual level, together with the collective dynamics of cell lines, communities, and ecosystems [66].

CARDIOLOGY

The primary diagnostic tools accessible to cardiologists are the heart's electrical impulses, as measured by electrocardiography (ECG), and heart auscultation. Machine learning technologies have facilitated signal analysis and classification for both the preceding and subsequent instances.

The cardiologist often does cardiac auscultation with a stethoscope. A digital stethoscope, or phonocardiogram (PCG), may capture these signals, which may then be analysed using machine learning algorithms to identify aberrant sounds. In 2018, [67] introduced a machine learning-based system that identifies cardiac signals and diagnoses cardiac diseases with 97% accuracy.

Furthermore, ECG signals interpreted by cardiologists on paper can be digitised into computers as numbers denoting line amplitude at each timestamp. These values can serve as input for the algorithm/structure that analyses the signal pattern and then classifies it.

Earlier this year, [68] introduced a machine learning model capable of classifying ECG signals and detecting arrhythmia using a single lead, whereas cardiologists typically require analysis of all 12 leads for a comprehensive ECG assessment. This model attained a sensitivity of 92.7% and a positive predictive value of 86.1% for ventricular ectopic beats, utilising lead II, and a sensitivity of 95%. 7% and a positive prediction value of 75.1% when utilising lead V1.

OPHTHALMOLOGY

Whether pertaining to visual impairment or ocular illness, the intricate domain of ophthalmology has seen a significant number of machine learning applications [69,70].

Ophthalmologists already utilise technology to swiftly and efficiently diagnose visual problems. Regarding other illnesses, concerns are to the repercussions of diabetes mellitus affecting the eyes, namely diabetic retinopathy (DR). [71] shown that employing a deep learning system enables professionals to assess diabetic retinopathy more swiftly and accurately.

Furthermore, [72] have recently introduced a CNN model that employs an attention-based strategy for glaucoma detection, surpassing existing state-of-the-art approaches.

The intricate domain of ophthalmology has witnessed a considerable number of machine learning applications, whether pertaining to visual abnormalities or ocular conditions [70-86].

Ophthalmologists are utilising technology to swiftly and effectively detect visual problems. Many concerns regarding various illnesses pertain to the ocular consequences of diabetes mellitus, including diabetic retinopathy (DR). Sayers and colleagues demonstrated that employing a deep learning system can enhance the speed and precision with which doctors judge diabetic retinopathy (DR). Conversely, a convolutional neural network model that utilises an attention-based technique for superior glaucoma detection compared to existing methods state-of-the-art techniques [87-90].

CONCLUSION

From the perspective of physicians evaluating the present state of machine learning and artificial intelligence in healthcare, the inquiry is whether we are prepared to fully integrate this technology into our practice. Numerous difficulties persist in the complete integration of these technologies within the healthcare sector. This encompasses the necessity for legal and ethical rules and frameworks addressing key circumstances. Multi-tiered training designed to equip physicians with the requisite background on this matter. Technology is essential. Furthermore, the inquiry pertains to the safe and humane integration of it into routine clinical practice. What is the appropriate infrastructure for the implementation of these systems? Furthermore, financial stress is a significant consideration, particularly during the first period [73]. Such solutions would enhance efficiency for clinicians, save time and effort while aiding in the decision-making process. Due to the vast quantity of instances utilised for training these systems, their insights surpass the cumulative experiences of any individual physician and can provide significant advantages [74]. AI, either independently or in conjunction with ML, appears to be a potent answer for improving the quality of personalised medicine and expediting the advancement of intricate diagnostic and therapeutic methodologies, particularly in genetics, small molecule, and super target treatments.

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