Review Article

Artificial Intelligence in Laboratory Medicine

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Abstract

Artificial intelligence has found its way into virtually all human endeavours and the spectrum of engagement keeps enlarging. Art, finance, data analysis, automobile, cybersecurity, and healthcare have all benefitted from the enormous remodelling artificial intelligence has brought to those fields. Laboratory medicine is a branch of the medical practice involved in taking samples from the human body and examining them to determine patients' diagnosis and aid in administering the appropriate treatment. Existing literature was reviewed to identified how well laboratory medicine has utilized artificial intelligence in its operations. Anatomical pathology, chemical pathology, haematology, and clinical microbiology specialties of laboratory medicine have embraced artificial intelligence, deploying several tools into almost all the phases of the total testing process. They have incorporated machine learning, deep learning, artificial neural network and several other tools into electronic medical records, screening, diagnosis, and data curation. This has led to a great improvement in the quality of work and turnaround time in most of the laboratories. Although there are challenges currently limiting the deployment of artificial intelligence in these specialties, there is a continual effort at circumventing them, and improving service delivery to the end users. It is expected that the expansion in the technological spectrum in all the phases of laboratory practice will continue to improve workflow and efficiency of laboratories in the provision of quality services to patients and clinicians.

Keywords: Artificial Intelligence, Laboratory medicine, Laboratory, Deep learning, Machine Learning, Large language model

INTRODUCTION

The ability of computers to carry out tasks that ordinarily need human intelligence is known as Artificial Intelligence (AI), and its importance in the world is continually growing. Although the medical field was slow to adopt AI, its application is growing quickly, and in the years to come, promises to completely transform patient care. Nearly all specialties of medicine have embraced different levels of AI in the delivery of their services for optimum patients' care. Cardiology,

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radiology, ophthalmology, surgery, gastroenterology and oncology amongst so many other medical specialties have deployed AI into screening, diagnosing, treating and performing surgical operations as it relates to each of them.[1] Furthermore, almost all sections in a hospital workflow have created a niche for AI in order to hasten processes which had always been handle manually with considerable time wastage and delay in service delivery. Processes like electronic medical records, ~~to~~ prioritization of at-risk patients, personalization of treatment recommendation, detection of fraud, waste and abuse have all been incorporated into one AI tool or the other. [2] This review is aimed at highlighting the extent to which laboratory medicine has utilized AI.

Laboratory medicine comprises four major specialities including haematology, anatomical pathology, chemical pathology, and medical microbiology. Each of them combines clinical practice with provision of wholistic laboratory services, having the ultimate aim of improving patients' diagnosis. The advent of AI has not only revolutionized the practice of medicine, but it has also begun to infiltrate some of the traditional processes involved in the practice of laboratory medicine. Some of the laboratory instruments are now fully automated with performance level better than those of human operators. In addition, the huge amount of data usually generated by the laboratories has been incorporated into AI platforms to produce discrete patterns which has significantly improved clinical decision support systems with great potential to improve health outcomes and decision-making processes. [3] Each of the four specialties of laboratory medicine has peculiarities for which AI has been deployed, and this has led to drastic reduction in human errors, improved accuracy of laboratory results and turn-around time.

Artificial Intelligence in Haematology

In the field of haematology, AI has been deployed to several sectors of the practice to enhance and facilitate service delivery to patients. Within the last decade, machine learning has been used to design predictive modelling for several haematological cases. In terms of treatment outcomes, patients who had chronic lymphocytic leukaemia, Hodgkin's lymphoma and acute myeloid leukaemia can now benefit from validated prediction models and machine learning algorithms to predict infection risk, relapse and remission following the institution of treatment protocols. Examples include CLL Treatment-Infection Model (CLL-TIM), PET Radionics Model, etc [4-6] Furthermore, risk of mortality in certain haematological diseases can now be predetermined using several algorithms created for the purpose. For example, the European Society for Blood and Marrow Transplantation developed a risk scoring system for predicting mortality in patients who had allogeneic stem cell transplant using a machine learning algorithm. [7] Similarly, the MIPSS70 model was designed as a risk stratification tool for patients with primary myelofibrosis, essentially to predict overall survival for those patients. [8]

In the area of clinical diagnosis of haematological disorders, artificial neural network technology has been deployed, using pattern recognition and data mining systems to read peripheral blood film, flow cytometry graphs and bone marrow slides of several haematological diseases. The output in each of these three achieved an excellent comparison with physician's report with-improved turn-around time. [9] In addition, AI-based image analysis systems have been used to analyse images from radiology scans, histopathology slides and nuclear medicine data of various haematological diseases with impeccable precisions. These systems were able to count total blood cells and the differentials and also detect abnormal cell morphology and inclusion bodies within the cells. [10] Most of the platforms used are based on deep-learning techniques which have been supported with numerous data from clinical and laboratory repertoire. [11, 12]

Artificial Intelligence in Anatomical Pathology

Anatomical pathology uses microscope to examine tissues and/or cells to diagnose and investigate disorders of the tissues or manifestation of pathologies. It plays a critical role in the diagnosis, staging, prognostication, and categorizing of malignancies. The application of AI holds immense capacity to aid experts in pathology in performing these functions. For example, deep learning algorithms have been deployed to forecast genetic changes using the traditional hematoxylin and eosin (H & E) images from which genomic-related data are extracted. [13,14] Furthermore, a convolutional neural network (CNN) system that can accurately forecast genetic mutations in many cancers such as KRAS, EGFR, TP53, FAT1, STK11, and SETBP1 has been developed, using data extracted from H & E images in malignancies of the lungs, breast, stomach, colon, and the rectum. [15] In addition, microsatellite instability testing which was not routinely done due to the cost and technicality involved, can now be determined from traditional H & E stain using a deep learning technology. This is particularly beneficial to patients with gastrointestinal cancer in determining their potential response to immunotherapy. [16]

Artificial intelligence can clearly and succinctly predict disease outcomes and responses to interventions by providing information premised on histological features using deep-learning prediction models. [17,18] With its adept ability to match pertinent histological variables including type of neoplasm, the morphology of the stroma, lympho-vascular permeation, and individual nuclear characteristics, AI algorithms that are photocentric can fabricate a comprehensive method of categorization that can predict treatment outcomes, in addition to the possibility of invasion, metastases or even recurrence. [13] Furthermore, convolutional neural networks (CNN) have been used for the images from the Atlas of The Cancer Genome, to determine the structural dimensions of tumour-infiltrating lymphocytes (TILs), which had prognostic values in more than 10 malignant lesions subclasses reported. [19]

Artificial intelligence can be deployed into quality control management in the pathology laboratory. For example, AI can be used to validate the sufficiency of neoplastic tissue before it goes into further processing.[20] AI tools can be harnessed to triage cases for inappropriate sections of tissue or to prioritize certain tissues over the others before sending them for review by pathologists. They can also be applied to aid with the inspection of unanticipated occurrences such as contamination of tissues and presence of artifacts. For proper archiving, preservation, and retrieval of pertinent data when the need arises, stained tissue slides computerization will be handy. [21] Furthermore, AI can be incorporated into the workflow of laboratory reporting thereby giving trainees extra access into multiple databases to aid learning. [21] In addition to improving training, AI also enhances consults between subspecialties thereby making inter-institutional collaborations easier and making for effectual consults and provision of second opinions in difficult cases. [22]

Artificial Intelligence in Chemical Pathology

The total testing process in chemical pathology or clinical chemistry is divided into three phases, and each of them has been impacted by the recent development in AI. In the pre-analytical phase, a common source of error is the inappropriate filling of request forms and Wrong Blood in the Tube (WBIT), when the blood in the sample collection tube does not match the unique patient identifier on the tube. [23] To address this problem, the artificial neuron network technology was deployed, using anonymized data from the Laboratory Information System (LIS) simulating mislabelled samples. It was able to identify mislabelled samples with an accuracy of 92%, outperforming trained laboratory professional by over 15%. [24] AI can also detect samples that have been contaminated by intravenous fluid, a cause of preanalytical errors with potential catastrophic medical consequences. This was tested using a Uniform Manifold Approximation and Projection (UMAP) model that was trained using both real patient data and synthesized data of IV fluid contaminant. [25] However, this model has a low positive predictive value (PPV) and it lack explainability resulting in scepticism and delays in adoption.

In the analytical phase, AI has been deployed to solve the problem of laboratory test overutilization. Overutilization is the over-ordering of tests whereby tests are requisitioned even though they are not indicated. It is fast becoming a source of concern for laboratory physicians; a recent study put the rate of occurrence as 20.6%. [26] For example, the decision Tree (DT) model was trained using supervised learning utilizing published datasets and in-house test results to predict the diagnosis of Thrombotic thrombocytopenic purpura a rare form of thrombotic microangiopathy, thus eliminating the excessive requisition of ADAMTS13, an enzyme whose deficiency is associated with the disease. [27] Similarly, machine learning technology has been deployed to circumvent expensive and time-consuming tests such as the ultracentrifugation method for quantification of low-density lipoprotein cholesterol. Deep Neural Network and Transfer Learning were trained using Total Cholesterol, High-Density Lipoprotein Cholesterol, Triglycerides, and Low-Density Lipoprotein Cholesterol data from Electronic Medical Records to predict LDL-C. This outperformed both the Friedewald and Martin Hopkin's equations which are traditionally used for the same purpose, despite their shortcomings. [28]

In the post analytical phase, Large Language Models (LLMs) like Chatbot that simulate human conversation utilizing Natural Language Processing are set to play a huge role in clinical chemistry laboratories ranging from interpretation of laboratory tests to detection of frequently encountered pre-analytical, analytical, and postanalytical errors that could enable quick troubleshooting of laboratory processes. The performances of ChatGPT 3.5 and GPT-4 when challenged with 35 real-life case scenarios, clinical consultations, and clinical chemistry testing questions were compared with those of senior Chemistry faculty, junior Chemistry faculty, fellows, and residents. ChatGPT4 had similar performance as the clinical chemistry residents. [29] LLMs are still hampered by a lack of human-like reasoning abilities and AI Chatbot hallucinations in which they present misinformation, inconsistencies, and falsities as factual and correct. [30]

Artificial Intelligence in Medical Microbiology

AI has emerged as a promising tool in clinical microbiology, particularly in the areas of diagnostic testing and image analysis. [31] AI has been deployed for the identification of mycobacteria and bacteria colonies, stool, and blood parasites amongst others. [31, 33] In order to enhance the detection of growth on chromogenic media used for screening and classification of mixtures using urine chromogenic media, software has been developed to identify rare events from culture plates. [34] This technology achieved a sensitivity of 99.8% in detecting bacterial colony growth, but a lower specificity of 68.5% compared to manual reading. These solutions employ colony detection, enumeration, and classification, and utilize expert rules to create decision trees based on colony characteristics such as colour and variety. Furthermore, AI was applied in matrix-assisted laser desorption-ionization/time of flight mass spectrometry (MALDI-TOF) for the analysis of mass spectra data in identifying culture colonies and drug resistant organisms, thus enhancing the efficiency and quality of diagnostic testing. [35]

Another utilization of AI in the clinical microbiology lab is in the automated interpretation of respiratory Gram stains, where it can quantitatively assess and differentiate between various cell morphologies. Additionally, AI can be beneficial in analyzing other complex processes such as fluorescent acid-fast bacillus smears, fungal adhesive tape preparations, and stool trichrome smears. The ability of AI to generate information is of great importance, as it provides relative probabilities for each potential classification. This allows for the provision of more detailed information, including subtle differences in organism shape and size, which could lead to significant diagnostic distinctions. For example, AI has the capability to distinguish between different types of bacteria based on their visual characteristics. [31]

Limitations

The adoption of AI into day-to-day laboratory activities has been met with several challenges. Most of the technologies deployed require the storage of a large amount of data and images necessitating data compression in order to reduce the size. This compression, however, has a drawback in that it can lead to the introduction of pictorial artefacts which can culminate in the distortion of the pixel's general standard. [36] Moreover, the interconnectivity between different platforms in the course of AI system creation and utilization can interfere with the quality of data. [37] However, standardization and drawing up computational pathology (CPATH) data can be deployed to reduce the impact of these technical variability. Likewise, the inability of deep learning technology to show how they arrived at their conclusions, referred to as the 'black box' issue, is a source of concern to many. Although deep neural networks have the conspicuous advantage of proficiency and correctness, it is still confronted by stinging denunciation owing to their interpretability inadequacy, and this is a fundamental blockade in their adoption within the clinical community. Thus, future strategies are needed to elevate the explicability of artificial intelligence algorithms. [38] Lastly, the financial implication of AI adoption is enormous and may put more pressure on the budget of most hospitals, especially in developing countries where logistics and electricity remain a major problem.

CONCLUSION

Artificial intelligence has remarkably impacted the practice of laboratory medicine improving the effectiveness of laboratory workflow and the quality of services provided within a shorter time frame in all the known specialties. However, there are multiple drawbacks in its application in the total testing process, these are currently being unravelled. The future of AI in the laboratory medicine is very promising and it is expected to further improve the delivery of laboratory services to all end users.

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