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Revolutionizing Microbial Infection Diagnosis: The Role of Artificial Intelligence

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ABSTRACT

Artificial intelligence (AI), described as computer algorithms that exhibit cognitive characteristics like learning abilities, now affecting our lives in many areas. In the medical field, AI-supported image analysis has already taken on a central role in pathology, radiology and dermatology. The policy of this review consisted of peer-reviewed literature annotated in the Web of Science, Scopus, PubMed and Google Scholar databases. Articles were reviewed that describe the use of AI to analyze images to diagnose infectious diseases. Digitization in healthcare is already having a profound impact on patients. It is expected that the development that has started will continue to gain momentum. Machine learning is fundamentally changing the way we interact with health-related data, including clinical microbiology and infectious disease data. We will likely transition from the Internet of Things environment to the Internet of Bodies with devices and providing detailed health data even in disease-free times. The focus of this study was to review current views on attempts to apply AI methods in daily practice, as well as to search for promising methods to diagnose infectious diseases in the most efficient way.

Keywords: Infectious Diseases, Artificial intelligence, Diagnosis Healthcare, Clinical Microbiology

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1. Introduction

AI, defined as a computer algorithm that exhibits cognitive properties such as the ability to learn. AI-supported image analysis already plays an important role in pathology, radiology and dermatology. In the realm of genomics, intelligence is harnessed to forecast phenotypes based on genotypes **(1, 2)**. AI computational algorithms frequently depend on sophisticated machine learning (ML) methods, encompassing natural language processing and computer vision. AI classification can be categorized into analytical, human-inspired, and human-inspired AI based on the types of intelligence they demonstrate. Alternatively, AI can be classified as generic or super-artificial, depending on their evolutionary stage. All these categories share a common characteristic, which is that AI is frequently not recognized as such when it is employed in a broad sense. This occurrence, known as the AI effect, arises when observers disregard the actions of an AI system by arguing that it does not possess genuine intelligence. The concept that any technology that reaches a certain level of advancement becomes indistinguishable from magic holds true **(3, 4)**. Arthur Clarke famously stated that once one gains a comprehensive understanding of technology, the enchantment surrounding it inevitably fades away. Subsequently the 1950s, professionals have periodically forecasted the imminent arrival of comprehensive AI systems that exhibit human-like behavior across all domains of cognitive, emotional, and social intelligence. The veracity of these predictions remains to be seen. However, to gain a more comprehensive understanding of the potential of AI, we can examine it from two perspectives: the trajectory already traversed and the uncharted territory that lies ahead **(5, 6)**. The aim of this study is reviewed the role of artificial intelligence in microbial infection diagnosis.

History of AI

The history of AI is shrouded in uncertainty, but it is believed to have originated in the 1940s with the publication of Isaac Asimov's short story, Runaround. An overview of the evolution of AI is presented in Table 1.

Table 1. The history of artificial intelligence

Years	History of artificial intelligence	Reference
1942	science fiction writer *Isaac Asimov* published his short story Runaround	**(5)**
1950-1952 **Alan Turing**	Construction of the first electromechanical computer Describing the “Imitation Game”, a game of deceit between a man and a machine	**(7)**
1952 **Marvin Minsky *et al*.**	Establishment of artificial intelligence laboratory at MIT University	**(5)**
1956	Defined as the study of ‘intelligent agents.	**(8)**
1956	Artificial intelligence (AI) was first described by John McCarthy at Dartmouth College.	**(9)**
1956	AI has been described as the "fourth industrial revolution".	**(9)**
1960	The researchers at Stanford University developed the first problem solving program, “Dendral”, whose purpose was to evaluate hypotheses.This first system was used to identify the bacteria causing serious blood infections and recommend appropriate antibiotic therapies	**(10)**
1975-Edward Shortleaf	MYCIN was the first, AI expert system (also known as knowledge-based systems), to provide consultation and diagnosis for antimicrobial therapy.	**(11)**
1953-1993 **Miller**	PIP- Present Illness Program (acquires the diagnosis of patients with renal disease) INTERNIST-1- internal medicine diagnosis by modeling behavior of clinicians, CASNET (Casual Associated Network)- for Glaucoma assessment and therapy, PUFF- Pulmonary function test interpretation. Miller has done a review on medical expert systems.	**(11)**
1995-2004 **Shu-Hsien Liao**	Conducted a review on expert systems	**(11)**

2. Discussion

Advances in AI from the beginning until now in medicine

In the field of medicine, AI has emerged as a powerful and promising tool among existing analytical methods **(12)**. While most health-related research can be supported by statisticians and bioinformatics experts, the advent of omics has generated vast amounts of data on gene polymorphisms, gene expression, metabolism, lipidomics, and proteomics, necessitating the development of more sophisticated apparatuses to recognize detailed cases from the global data volume. The use of AI in infectious disease management has improved diagnosis and prevented transmission, with mathematical models proving effective in predicting the magnitude of emerging infectious diseases **(13, 14)**. In recent years, there has been a significant advancement in the development of predictive models and big data sets for non-communicable diseases. These diseases include hypertension, heart disease, and diabetes. A comprehensive study was conducted, gathering data from all fifty states in the United States over a span of five years **(15)**. The emergence of life-threatening epidemics, such as Ebola and SARS-CoV-2, has instigated a wave of innovation in the realm of prediction. Various techniques, including machine learning, single-layer artificial neural networks, logistic regression, decision trees, and SVM classifiers, have been employed to develop a range of predictors. These predictors can be effectively utilized to analyze diverse combinations of Ebola-related data **(16-18)**.

Clinical laboratories are increasingly automated, with advanced robotics and software with AI capabilities being integrated into orchestration lines (19, 20).

The utilization of automated equipment has enabled robotic systems to perform procedures that were previously carried out by laboratory assistants in a swift and efficient manner. The implementation of contemporary automated systems for sample storage in method analysis can significantly augment the capacity of transparent tests (21). The intelligent Internet of Things for disease monitoring presents a viable solution for effectively monitoring diseases and detecting various forms of the ailment. The proposed plan entails a vast network of smart devices that will automatically process and interpret the entered data, which will then be transferred to the main backend, potentially the Ministry of Health data. This system will function as an initial alert mechanism to monitor the dissemination of illnesses. Once the trends and analysis are identified, it becomes easier to take action to curb the rapid spread of the disease and contain it across the country and globally. Additionally, it enables patients to identify the disease at an early stage (22). To address this pressing issue, many individuals are utilizing the Internet of Things to collect real-time sensory data, which was not feasible until recently. This involves monitoring individuals, medical facilities, the environment, and even remote areas of the world in certain circumstances (23). General AI and its subset, machine learning (ML), have demonstrated their immense value in analyzing data-rich sources, including macro or microscopic images, Matrix-assisted laser desorption ionization–time of flight mass spectrometry (MALDI-TOF MS), and whole bacterial genome sequences. The application of AI in clinical microbiology has already yielded significant benefits, as it has provided valuable assistance to laboratory personnel in various aspects of diagnostic testing. The improvement of AI tools, the enhancement of analysis accuracy and dependability by AI software, and the integration of AI into clinical microbiology labs' workflow are all bound to progress in the future. Consequently, microbiologists will increasingly depend on AI for initial screening or regular analysis of infectious disease tests. This will enable them to dedicate their attention to diagnostic complexities, such as intricate engineering and laboratory quality monitoring. The implementation of these modifications will improve the effectiveness and excellence of laboratory testing in clinical microbiology, which will have positive outcomes for both the laboratory itself and the patients it serves (24, 25). The advancements in microbiological technologies are rapidly transforming the ability to diagnose infections, enhance patient care, and streamline clinical workflows. These innovative tools broaden the scope, depth, and speed of diagnostic data and tests generated by patients, bringing them closer to the patient through the utilization of rapid diagnostic technologies such as point-of-care (POC) technology. Despite the significance and potential of these novel technologies, there exists a gap between clinicians and certain payers and hospital management in terms of recognizing their clinical usefulness. Consequently, a primary obstacle for the clinical microbiology community is to effectively communicate the value proposition of these technologies in order to encourage payers and hospitals to adopt advanced microbiology testing. The provision of specific guidance on how to define and demonstrate clinical utility would be immensely advantageous (26, 27). Within the field of medicine, there exist two distinct categories of artificial intelligence: virtual and physical, the latter of which pertains to robotics. The virtual classification pertains to mathematical algorithms utilized for the purposes of diagnosis and prognosis, imaging and osteoporosis, appointment scheduling, dosing algorithms, drug interactions, and electronic health records. The physical feature, on the other hand, encompasses robotic assistance in surgical procedures, telepathy, rehabilitation, and social assistance robots utilized in the care of elderly patients (28, 29). AI has predominantly been employed in the field of endodontics through virtual means, specifically in the finding of periapical lesions, crown and root fractures, purpose of working length, and recognition of morphology. In the 1970s, certain AI-based methodologies were introduced to elucidate diseases, electrocardiography, facilitate the selection of appropriate treatment, and assist clinicians in generating hypotheses pertaining to complex diseases (30, 31). AI-based technologies are employed to collect personal health information from patients, which is then utilized to generate a comprehensive knowledge dataset. This dataset aids clinicians in making well-informed decisions and developing personalized treatment plans for their patients. The primary objective of AI-based healthcare technologies is to analyze the effectiveness of disease treatments, disease prevention strategies, and their respective outcomes for patients. To accomplish this, various approaches such as ML, convolutional and deep neural networks, and Bayesian networks are implemented to enhance healthcare through intelligent computing systems. The recent advancements in information and communication technologies have led to a substantial increase in the volume of data gathered from public health surveillance. By integrating AI-based tools with reliable disease management platforms, it is possible to establish robust analytics that empower stakeholders to effectively respond to outbreaks of infectious diseases. In the past, confirming a tuberculosis diagnosis was a laborious and time-consuming process that posed challenges for global control efforts. However, presently, an AI-based tool, an artificial immune detection system, has been largely successful in achieving an early detection system for tuberculosis (28). Similarly, ARIS has facilitated the advent of AI-helped finding in various challenging infections. Additional illustration of AI application in human healthcare is its efficacious application in the precise finding of malaria. This is a straightforward mechanical system that bypasses intricate processing and marking protocols, thereby aiding clinicians in mitigating possible mistakes (32, 33). AI created technologies have demonstrated successful application in the field of epidemiology pertaining to infectious diseases, including but not limited to Kyasanur Forest Disease, Chikungunya, Middle East Respiratory Syndrome (MERS), Zika, and Ebola (34). AI algorithms that are capable of predicting the genome and protein ultrastructure of successive virus generations can prove to be of significant value in preparing for potential viral infections. The application of such algorithms to datasets of the Newcastle disease virus in China and South Korea has resulted in the prediction of mutant nucleotides with an accuracy rate of 70%. (35). AI-based methodologies have been fulfilled in the diagnosis of COVID-19. Certain AI-based tools have proved effective organization of the severity of COVID-19 through the use of radiological images, such as CT scans and X-rays (36). Various machine learning algorithms, such as Convolutional Neural Network (CNN), linear discriminant analysis, naive bayes, vector machine support, decision trees, logistic regression, and random forest, are utilized to diagnose COVID-19. These algorithms make use of diverse datasets to classify images into different groups, thereby assisting in determining the severity of the disease and distinguishing COVID-19 from other similar diseases that exhibit comparable symptoms and pneumonia (37, 38).

Types of programs used in AI

AI is a dynamic and continuously evolving field of computing research that aims to develop systems capable of simulating human intelligence and performing tasks such as visual awareness, decision making, speech recognition, and natural language processing (39, 40). The development of AI is driven by two key factors: the availability of electronic health record data and advances in computing power. These factors are closely related to complex mathematical functions, namely ML or NN (41). The advent of Deep Neural Network (DNN) architectures has further increased the complexity of AI over the past decade (42).

ML, a subset of AI, distinguishes itself from expert systems by its capacity to adapt in the face of extensive data. Unlike expert systems, which are manually defined using human expertise, ML operates without the need for human intervention and strives to autonomously acquire rules, akin to the functioning of the human brain. This characteristic renders ML less vulnerable and less reliant on human experts (43). NNs, on the other hand, are computational models that employ mathematical calculations and are inspired by the workings of biological neural networks. Comprising interconnected information links, NNs possess the ability to identify underlying relationships within a vast amount of data. A DNN, specifically, encompasses multiple layers of processing units, enabling enhanced data predictions and independent learning (42). AI has the potential to revolutionize clinical decision making by effectively managing the extensive amount of data associated with a patient's care and medical history. However, many healthcare professionals still do not fully comprehend the advantages of AI and continue to rely solely on their personal experience and treatment guidelines when making decisions (41). ML was created to address the limitations of expert systems (40). In ML, engineers design algorithms that can establish their own rules based on data, replacing manually coded rules by humans. This enables ML systems to learn from data and interpret unfamiliar situations. Among the various ML techniques developed, deep learning, which relies on artificial neural networks, is the most well-known (9). AI-driven medical devices have been developed and are currently being utilized in clinical settings for a range of tasks, such as analyzing medical images, conducting omics analysis, and processing natural language for drug discovery, electronic health record information, and literature searches (44, 45). Additionally, AI is actively employed in vaccine development, the creation of new diagnostic methods, and the development of novel therapeutics by extracting crucial information from vast amounts of AI data in ongoing COVID-19 research (46). Fully automated diagnostic pipelines and machine learning have gained a foothold in various fields of clinical medicine, including clinical microbiology. Next-generation sequencing (NGS) techniques allow for insight into pathogens by analyzing millions of tiny fragments of their genome and even gaining insight into the composition of the microbiota. Automation combined with novel technologies can make a difference to traditional clinical microbiological tests, which often need an important quantity of physical work. However, the impact of these advances on clinical routine in terms of sample-to-outcome time, resources and management, and interpretation of large multimodal data subsequent from these novel technologies is still being studied (47, 48).

Commercially available instruments, such as the WASPLab™ by Copan and the Kiestra TLA by Becton Dickinson, offer automated culture-based assays that encompass tasks such as sample streaking, slide preparation, and the transfer of intermediate inoculated media. These instruments also include instrumentation and automated incubators (49). By utilizing these systems, the number of manual pre-analytical, analytical, and post-analytical steps typically conducted in a non-automated laboratory can be significantly reduced. Moreover, studies have demonstrated that these automated systems enhance the processing of samples and decrease the time required to obtain results (50). Furthermore, the complete automation of diagnostic procedures holds the potential for additional advantages (47).

Clinical applications

An ideal clinical application in the realm of microbiology is characterized by its ability to expedite and ensure precise identification of the microorganisms accountable for causing an infectious disease in a patient. This, in turn, allows for the timely administration of the appropriate treatment. ML has the potential to achieve precise diagnoses with the aid of suitable input data, which is contingent upon the extent to which the sample or patient sample can be digitally represented. Microscopic image data is a widely accepted format for this purpose (51). A comprehensive review has elucidated the typical conversion of image data into units that serve as input for machine learning methods. Although the conventional method of examining thick and thin blood smears under a microscope is considered the most reliable technique for diagnosing malaria, recent research has investigated the advancements in automating malaria diagnosis using image analysis. To achieve this, machine learning methods have been combined with computer-aided diagnostic software (CADx) that utilizes image analysis. This approach aims to facilitate the process of diagnosing malaria through automated means. Nevertheless, the analysis of image variations, also known as "hand-designed features," still requires human expertise. To address this, researchers have utilized convolutional neural networks (CNNs), a type of deep learning model, for image analysis. These CNN models have been successfully applied in studies to classify parasitized and uninfected malaria cells by employing pre-trained models as feature extractors and conducting patient-level cross-validation. Additionally, pilot studies have been conducted to assess the effectiveness of deploying CNN models on mobile devices. This approach holds promise in reducing delays in disease-endemic or resource-constrained settings. Similarly, a trained CNN model was able to differentiate scanned images of stained parasitic fecal swabs from those that did not, thereby reducing the workload of lab workers and increasing sensitivity compared to examining human slides alone (52, 53).

Challenges Faced when Using Machine Learning

The use of ML has its own set of advantages and disadvantages, similar to other statistical methods in the field of biology. However, these drawbacks can be partially mitigated by carefully selecting the problem or question to be examined. It is crucial to meticulously choose the outcome variables and covariates in order to optimize the application of ML. ML algorithms are most suitable for questions that concentrate on a specific population, where the influence of covariates on the risk of selected outcomes is expected to be relatively consistent within a well-defined population group (54). This population group is often defined by certain disease states or microbial species. Nevertheless, if the populations under analysis are not well-defined or if the characteristics of the population exhibit high variability, ML may encounter challenges. Additionally, since ML's effectiveness is limited by small sample sizes, either the population being studied must be sufficiently large for the diseased cohort or the sample size must be large enough to leverage the capabilities of ML (55).

Application of AI in the diagnosis of infectious diseases

As a consequence of the aforementioned issue, the Global Influenza Surveillance and Response System (GISRS) has monitored the evolutionary mechanisms of influenza viruses (13). Artificial intelligence (AI) programs have been acknowledged as conventional tools for detecting early indications of infectious diseases and have become one of the fundamental principles of infectious diseases (56). AI is increasingly being utilized in laboratory medicine for various purposes, including the interpretation of antinuclear antibody (ANA) patterns and the analysis of white blood cells (57). Simple tree-based analytics rely on a set of predefined rules, such as CLSI or EUCAST interpretation criteria, and are often referred to as non-adaptive AI. On the other hand, adaptive AI can derive rules either from human input or machine discovery. These rules are then applied to new data to classify it. In the clinical laboratory, a simplified form of machine learning called linear regression is used to predict standard curves for instrument calibration. In regression analysis, a computer is provided with an equation and tasked with optimizing the values of variables to achieve the best possible representation, or prediction, for a two-dimensional data set showing analyte concentration versus assay reading. To illustrate some common machine learning terms, let's consider AI-based image analysis. While humans can easily interpret images due to the dedicated visual cortex in our brains, teaching a computer to understand images is a complex undertaking. Machine learning algorithms lack inherent knowledge of which data or features within an image are crucial for classification or diagnosis **(24)**. ML applications include risk stratification of specific infections, identification of disease risk factors, characterization of host-pathogen interactions, prediction of the emergence and spread of emerging pathogens **(6)**, and digital screening of bacterial cultures in agar **(58)** as well as review of Gram staining of blood cultures **(59)**. ML has been utilized in various studies to predict different aspects of infectious diseases. For instance, ML has been employed to forecast the risk of nosocomial *Clostridium difficile* infection, zoonotic reservoirs, outcome in Ebola virus infections, the risk of developing septic shock based on a severity score, and sepsis mortality. In a particular study conducted by Guilamet *et al*., cluster analysis was employed for risk stratification. Previous attempts to identify episodes associated with bloodstream infections have relied on predetermined classification groups based on known microbiological episodes, site of infection, and patient characteristics. However, the authors hypothesized that clinically relevant groupings may transcend these previous classifications, even within a heterogeneous population. To test this hypothesis, the authors applied cluster analysis to variables from three domains: patient characteristics, disease severity/clinical presentation, and infection characteristics. The resulting analysis yielded four stable cluster arrangements: Cluster 1 "Surgical transfers from the hospital," Cluster 2 "Functionally immunosuppressed patients," Cluster 3 "Women with skin problems and urinary tract infection," and Cluster 4 "Acute pneumonia." Notably, *Staphylococcus aureus* was predominantly distributed in clusters 3 and 4, while non-fermenting gram-negative bacteria were mainly grouped in clusters 2 and 4. Furthermore, more than 50% of the pneumonia cases occurred in Cluster 4. These findings highlight the potential of machine learning methods to identify homogeneous clusters in infectious diseases, surpassing traditional patient categories. By identifying new clinical phenotypes, these methods have the potential to enhance severity assessment and facilitate the development of new treatments for complex or chronic infectious diseases in Figure1 **(10, 60)**.

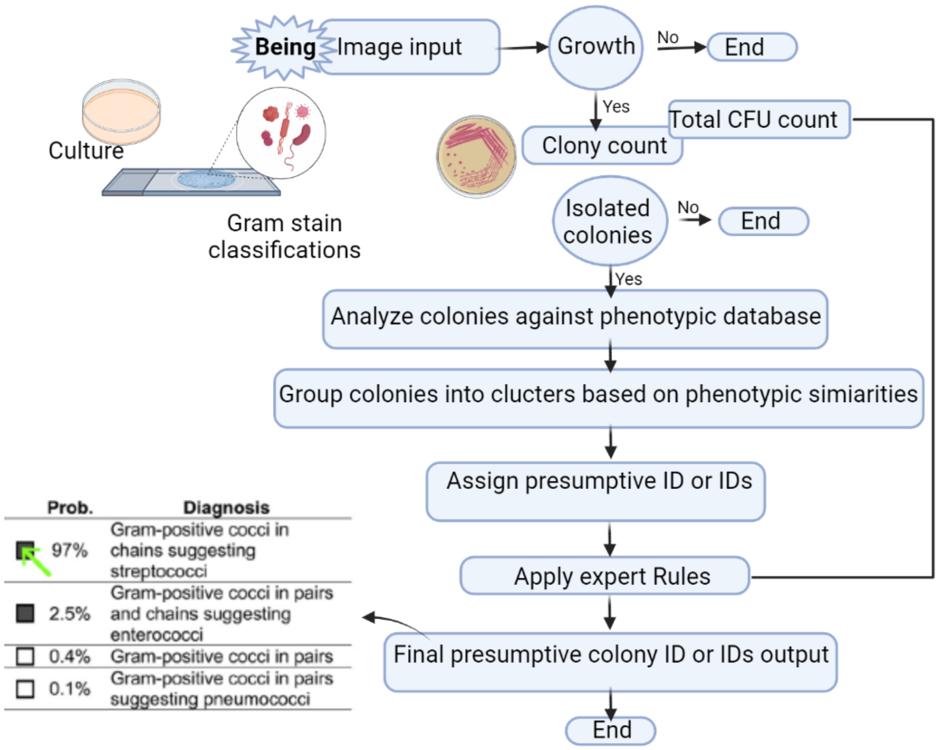

Figure 1. The algorithm diagnosis uses artificial intelligence in infection disease (Design by author from Biorender, 2024)

AI has been used in the diagnosis of diseases in clinical settings, a list of which is provided in Table2.

Table 2. AI and clinical trial in diagnosis of infectious disease

Title	Status	Conditions	Interventions	Phases	Locations/URL
Validation of Artificial Intelligence Enabled TB Screening and Diagnosis in Zambia	Recruiting	Tuberculosis			Zambia https://ClinicalTrials.gov/show/NCT05139940
Optimal Antibiotic Treatment of Moderate to Severe Bacterial Infections	Unknown status	Community-associated Infections|Health-care Acquired Infections|Nosocomial Infections	Other: antibiotic treatment of by TREAT/PCR	Phase 3	Israel https://ClinicalTrials.gov/show/NCT01338116
Development of an Artificial Intelligence System for Intelligent Pathological Diagnosis and Therapeutic Effect Prediction Based on Multimodal Data Fusion of Common Tumors and Major Infectious Diseases in the Respiratory System Using Deep Learning Technology.	Recruiting	Artificial Intelligence Deep Learning Pathology, Molecular Medical Informatics|Database|Lung Cancer|Pulmonary Tuberculosis|Covid19			China https://ClinicalTrials.gov/show/NCT05046366
PEMF Therapy to Treat Lingering Symptoms of Lyme Disease After Treatment With Antibiotics	Terminated	Lyme Disease|Lyme Neuroborreliosis|Lyme Arthritis|Unknown Origin Fever	Device: Scientific Consciousness Interface Operations (SCIO) Class II FDA approved medical device	Not Applicable	United Kingdom https://ClinicalTrials.gov/show/NCT04577053
Early Risk Assessment in Household Contacts (â‰¥10 Years) of TB Patients by New Diagnostic Tests in 3 African Countries	Recruiting	Tuberculosis	Diagnostic Test: New test candidates		Zimbabwe https://ClinicalTrials.gov/show/NCT04781257

AI and Gram Stain

In 2018, a study was conducted by Smith, Kang, and Kirby, focusing on the primary application of AI in the automated interpretation of Gram stains from blood cultures **(61)**. This approach, known as "transfer learning" in the field of AI, requires significantly fewer resources compared to starting the training process from scratch. Moving forward, advancements in bacterial microscopic analysis will involve training algorithms to interpret various bacterial morphologies and identify bacteria and fungi in primary samples stained with Gram. The identification of bacterial vaginitis, for instance, could be achieved by training software to recognize bacterial morphotypes and evaluate a Gram-stained swab using Nugent's scoring classifiers **(62)**. Additionally, swabs for acid-fast bacilli, calcofluor white KOH, and fungal preparations using phase contrast or lactophenol cotton blue could also be examined. All of these endeavors require supervised ML efforts, utilizing extensive training suites that have been successfully employed in other AI-based fields. The utilization of AI in Gram stain analysis is expected to enhance efficiency and accuracy, and we anticipate that it will bring significant benefits to the practice of clinical microbiology in the future **(24)**.

Application AI against Antibiotic Resistance

The utilization of AI techniques in the prediction, assessment, and diagnosis of infectious diseases in children, with a particular focus on drug resistance, as well as the efficient management of complications, is a subject of interest. Children exhibit a higher incidence of infections than adults and frequently present with non-specific symptoms, which results in diagnostic ambiguity **(10, 63)**.

Plate interpretation

The analysis of microbial growth on agar plates is a significant aspect of AI-based image interpretation in clinical microbiology. Unlike the automated imaging of slides, the integration of plate inoculation, handling, and imaging into existing MLA systems has already been achieved. However, there are still several challenges that need to be addressed in order to effectively incorporate AI-based interpretation of microbial growth into the overall laboratory automation workflow (64). The initial application of plate reading AI technology has been focused on two areas: detecting the presence or absence of growth in urine cultures and identifying specific target organisms of clinical or epidemiological importance on chromogenic agar plates based on the indicator's color. Notable examples include the AI-based detection of a chromogenic medium designed for Group A *Streptococcus*, vancomycin-resistant *Enterococcus*, and methicillin-resistant *Staphylococcus aureus* (61).

AI and Parasitology

Despite the advancements made in the detection of antigens, antibodies, and molecules for medically significant organisms, the preferred diagnostic method for most parasitic infections remains morphological analysis (13). The morphological detection of intestinal helminthes and protozoa, as well as blood-borne parasites like P*lasmodium* and *Babesia* Species, is commonly achieved through the microscopic examination of oocytes and parasites (O&P). This method is widely regarded as the "gold standard" in this field (61). However, recent advancements in computer vision technologies have shown promising potential in improving the reproducibility, accuracy, and overall performance of diagnostic microscopy. By utilizing computer vision algorithms, peripheral blood smears and trichrome-stained stool specimens can be analyzed more effectively, leading to enhanced detection, characterization, and quantification of parasites (24).

AI and Mycology

Machine Learning for Fungal Recognition

AI has recently caused a significant shift in the field of clinical medicine (65). Its ability to diagnose diseases is comparable to that of specialists in detecting diabetic retinopathy and skin cancer. Many dermatologists recognize the immense potential of AI in enhancing dermatological care (66). Currently, AI is primarily being researched in relation to skin cancer, ulcers, psoriasis, and other inflammatory skin conditions. It is also being used to predict skin sensitizing agents, conduct histopathological assessments, and analyze gene expression profiling (67). The creation of a comprehensive database consisting of a wide range of clinical images is crucial for training AI systems (67). Onychomycosis, a common condition with minimal racial variations, is an ideal candidate for AI implementation (68). Clinics worldwide can contribute to the database, ensuring that AI technology is not limited to specific populations. In 2018, Han et al. developed an AI system for diagnosing onychomycosis (69). Machine learning and computer vision techniques are rapidly advancing as tools to enhance mycological research and citizen science. However, their practical applications have mainly focused on classifying microscopic images of fungal spores (70). Tahir et al. (71) presented a dataset of 40,800 labeled microscopy images from six fungal infections and proposed a method to expedite medical diagnosis and reduce the need for costly additional biochemical tests. De Vooren et al. (72) introduced an image analysis tool that utilizes morphological features such as length, width, and other shape descriptors to identify fungal cultivars. Zielinski et al. (73) employed various CNN architectures and a bag-of-words approach to classify microscopic images of ten fungal species, eliminating the need for the final step of biochemical identification. This approach reduces both the cost and time required for identification. Additionally, AI has been applied to understand mycelial growth patterns and gain insights into fungal dynamics and cellular interactions (74). In recent times, there has been a growing fascination with employing AI as a means to assist citizen scientists and students in the identification of fungi. However, the practical implementation of such technology in real-world scenarios has been limited, with only a handful of instances documented thus far (75).

AI and virology

AI has the capacity to anticipate the transmission of the virus and establish early warning systems by extracting relevant information from social media platforms, phone calls, and news sites. This has the potential to offer valuable insights into regions that are vulnerable and forecast rates of illness and death. An example of this is Blue Dot, which employed machine learning to detect a cluster of pneumonia cases and predict the outbreak and geographical location of COVID-19 based on the data available. Health Map also gathers and shares publicly accessible data on COVID-19 to facilitate the effective tracking of its spread. In recent times, there has been an increasing emphasis on the role of AI in identifying and predicting COVID-19 outbreaks through the utilization of crowd-sourced and multimodal data (76, 77).

AI in contact tracing

AI possesses the capability to act as a beneficial addition to mobile health applications. The integration of smart devices, encompassing watches, cellphones, cameras, and diverse wearable devices, can be effectively utilized for the purpose of efficient diagnosis, contact tracing, and monitoring of the COVID-19 pandemic. An exemplification of this is the implementation of applications like AI for COVID-19, which rely on the analysis of two-second cough audio recording samples. These applications can be employed in the field of telemedicine, thereby enhancing the provision of medical care remotely (36, 77).

AI in monitoring of COVID-19 cases

AI methods are employed to manage patients in medical settings and predict the course of treatment. Through the analysis of data obtained from vital signs and clinical parameters, AI can provide essential information for allocating resources and making decisions by prioritizing the need for ventilators and respiratory support in the intensive care unit (ICU). Furthermore, AI can be utilized to predict the probability of recovery or mortality from COVID-19 and provide daily updates, memory and trend analysis, as well as record treatment history (77).

AI in reducing the burden from medical practitioners & healthcare staff

AI-powered triage systems have the potential to alleviate the burden on medical personnel and healthcare practitioners by automating diverse procedures. Additionally, these systems provide remedies that curtail their interaction with patients, thereby reducing the risk of transmission of infections (78).

AI in development of therapeutics

The utilization of AI techniques has the potential to enhance and supplement conventional technologies in the field of drug development. This is achieved by significantly reducing the duration required to bring a drug from the laboratory to the market through expediting lead detection, virtual screening, and validation processes. Additionally, AI can expedite the pace of drug development by extracting valuable data for drug reuse or repositioning by identifying the properties of previously approved and validated drugs based on descriptors and molecular properties, which may not be feasible for a human expert to accomplish. The application of machine learning methods in AI has facilitated the acceleration of drug discovery programs, as evidenced by the identification of baricitinib as a potential drug for the treatment of COVID-19 (79).

AI in development of vaccines

Humanity has not ever already observed such a fervent pursuit to create a vaccine for a pathogen. The velocity of scientific breakthroughs can be notably hastened by utilizing the capabilities of artificial intelligence. Ong and colleagues projected potential vaccine options for COVID-19 by employing the Vaxign reverse vaccinology machine learning platform, which is grounded on supervised classification models (80).

AI in curbing spread of misinformation

As a result of the overwhelming amount of information available, the current pandemic has transformed into an infodemic. Utilizing data from social media platforms such as Twitter and Facebook to comprehend the understanding, awareness, and practices associated with COVID-19 can aid in the development of a strategy to gather and distribute precise and timely information, thereby reducing the impact of the virus (77).

Challenge and future

The utilization of big data is an essential prerequisite for the training of artificial intelligence. In the healthcare sector, standardized data holds particular significance, especially when dealing with heterogeneous data from multiple regions, systems, and sources (55). While the dissemination of epidemic data is a positive stride, the scientific community has yet to achieve a consensus on specific datasets. Moreover, there is a scarcity of shared and collaborative datasets that are universally replicable and standardized for collaborative endeavors (81). It is imperative for governments, professional associations, and institutions at all levels to be encouraged to share validated data in order to bolster the advancement of AI algorithms (82). Another obstacle lies in the interpretability of AI, which encompasses the ability to scrutinize the rationales behind certain outcomes and the anticipation of potential failures (26). In the forthcoming years, one of the foremost challenges in implementing AI in the field of medicine will be the clinical validation of recently developed fundamental concepts and tools. Despite numerous studies already showcasing the utility of AI and its promising outcomes, there are several acknowledged limitations and frequently reported constraints that are likely to impede such validation efforts (83). With the advancement of speech recognition, AI-enabled computers could communicate with people in the future. In the near future, humans could become superhuman, and implants could be made from various missing body parts. With the aid of AI, climate change could be detected, making it easier to make predictions about the future (82).

3. Conclusion

Digitalization in healthcare is expanding. Machine learning is changing the way we interact with health-related data, especially in the fields of clinical microbiology and infectious diseases. We are likely to see a shift from the Internet of Things environment to the Internet of the Body, where implanted devices continuously provide accurate health data even during disease-free periods. In addition, advances in molecular diagnostics, such as metagenomics, add to the complexity of the data. In vitro diagnostics are expected to play an important role in the next decade. In the future, digital technologies such as personal assistants, internet-connected devices and bodies, smartphone technologies, self-driving vehicles, drones, and self-healing algorithms will undoubtedly shape our lives. Consideration for digitization and artificial intelligence in healthcare are high, driven by the need to optimize quality and reduce costs.

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No to declare.

Ethical Considerations

The study was approved by the Ethics Committee of Research & Technology of Hamadan University of Medical Sciences, Hamadan, Iran (ethic code: IR.UMSHA.REC.1401.642).

Authors' Contributions

HM and HH designed the topic and wrote the manuscript. HM and HH participated in the initial draft and the revision of the manuscript. HM revised the final version of the manuscript. All authors read and approved the final manuscript.

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Conflict of Interest

The authors declare that they have no competing interests.

References

1. Ghaderzadeh M, Hosseini A, Asadi F, Abolghasemi H, Bashash D, Roshanpoor A. Automated detection model in classification of B-lymphoblast cells from normal B-lymphoid precursors in blood smear microscopic images based on the majority voting technique. Sci Program. 2022;2022:1-8. [DOI:10.1155/2022/4801671]
2. Ghaderzadeh M, Asadi F, Ramezan Ghorbani N, Almasi S, Taami T. Toward artificial intelligence (AI) applications in the determination of COVID-19 infection severity: considering AI as a disease control strategy in future pandemics. Iran J Blood Cancer. 2023;15(3):93-111. [DOI:10.61186/ijbc.15.3.93]
3. Fasihfar Z, Rokhsati H, Sadeghsalehi H, Ghaderzadeh M, Gheisari M. AI-driven malaria diagnosis: developing a robust model for accurate detection and classification of malaria parasites. Iran J Blood Cancer. 2023;15(3):112-24. [DOI:10.61186/ijbc.15.3.112]
4. Gheisari M, Ghaderzadeh M, Li H, Taami T, Fernández-Campusano C, Sadeghsalehi H, Afzaal Abbasi A. Mobile Apps for COVID-19 Detection and Diagnosis for Future Pandemic Control: Multidimensional Systematic Review. JMIR mHealth and uHealth. 2024;12:e44406. [DOI:10.2196/44406] [PMID] [PMCID]
5. Haenlein M, Kaplan A. Guest editorial to the special issue, A brief history of AI: On the past, present, and future of artificial intelligence. Calif Manage Rev. 2019;61(4):5-14. [DOI:10.1177/0008125619864925]
6. Wiens J, Shenoy ES. Machine learning for healthcare: on the verge of a major shift in healthcare epidemiology. Clin Infect Dis. 2018; 66(1):149-53. [DOI:10.1093/cid/cix731] [PMID] [PMCID]
7. Naugler C, Church DL. Automation and artificial intelligence in the clinical laboratory. Crit Rev Clin Lab Sci. 2019;56(2):98-110. [DOI:10.1080/10408363.2018.1561640] [PMID]
8. Peiffer-Smadja N, Rawson TM, Ahmad R, Buchard A, Georgiou P, Lescure F-X, et al. Machine learning for clinical decision support in infectious diseases: a narrative review of current applications. CMI. 2020;26(5):584-95. [DOI:10.1016/j.cmi.2019.09.009] [PMID]
9. Aminoshariae A, Kulild J, Nagendrababu V. Artificial intelligence in endodontics: current applications and future directions. J Endod. 2021; 47(9):1352-7. [DOI:10.1016/j.joen.2021.06.003] [PMID]
10. Fanelli U, Pappalardo M, Chinè V, Gismondi P, Neglia C, Argentiero A, et al. Role of artificial intelligence in fighting antimicrobial resistance in pediatrics. Antibiotics. 2020;9(11):767. [PMCID] [DOI:10.3390/antibiotics9110767] [PMID]
11. Meraj SS, Yaakob R, Azman A, Rum SNM, Nazri AA. Artificial intelligence in diagnosing tuberculosis: a review. Int J Adv Sci Eng Inf Technol. 2019;9(1):81-91. [DOI:10.18517/ijaseit.9.1.7567]
12. Silver D, Schrittwieser J, Simonyan K, Antonoglou I, Huang A, Guez A, et al. Mastering the game of go

without human knowledge. Nature. 2017; 550(7676):354-9. [DOI:10.1038/nature24270] [PMID]

13. Agrebi S, Larbi A. Use of artificial intelligence in infectious diseases. Artificial intelligence in precision health: Elsevier; 2020. p. 415-38.[PMCID] [DOI:10.1016/B978-0-12-817133-2.00018-5]

14. Desai SA, Mahitha G. Ayurnano: A Solution Towards Herbal Therapeutics Using Artificial Intelligence Approach. In Artificial Intelligence for Innovative Healthcare Informatics. Cham, Springer International Publishing: Berlin, Chermany. 2022. pp. 247-62. [DOI:10.1007/978-3-030-96569-3_12]

15. Luo W, Nguyen T, Nichols M, Tran T, Rana S, Gupta S, et al. Is demography destiny? Application of machine learning techniques to accurately predict population health outcomes from a minimal demographic dataset. PloS One. 2015;10(5): e0125602. [DOI:10.1371/journal.pone.0125602] [PMID] [PMCID]

16. Abdulrazak A, Ibrahim Bitar Z, Ayesh Al-Shamali A, Ahmed Mobasher L. Bacteriological study of diabetic foot infections. J Diabetes Complicat. 2005;19(3):138-41. [DOI:10.1016/j.jdiacomp.2004.06.001] [PMID]

17. Roeding F, Borner J, Kube M, Klages S, Reinhardt R, Burmester T. A 454 sequencing approach for large scale phylogenomic analysis of the common emperor scorpion (Pandinus imperator). Mol Phylogenetics Evol. 2009;53(3):826-34. [DOI:10.1016/j.ympev.2009.08.014] [PMID]

18. Colubri A, Silver T, Fradet T, Retzepi K, Fry B, Sabeti P. Transforming clinical data into actionable prognosis models: machine-learning framework and field-deployable app to predict outcome of Ebola patients. PLoS Negl Trop Dis. 2016;10(3): e0004549. [DOI:10.1371/journal.pntd.0004549] [PMID] [PMCID]

19. Park JY, Kricka LJ. One hundred years of clinical laboratory automation: 1967-2067. Clin Biochem. 2017;50(12):639-44. [DOI:10.1016/j.clinbiochem.2017.03.004] [PMID]

20. Delaney NF, Rojas Echenique JI, Marx CJ. Clarity: an open-source manager for laboratory automation. J Lab Autom. 2013;18(2):171-7. [PMID] [PMCID] [DOI:10.1177/2211068212460237]

21. Chapman T. Lab automation and robotics: Automation on the move. Nature. 2003; 421(6923):661-3. [PMID] [DOI:10.1038/421661a] [DOI:10.1038/421661b]

22. Shaikh N, Shope TR, Hoberman A, Vigliotti A, Kurs-Lasky M, Martin JM. Association between uropathogen and pyuria. Pediatrics. 2016;138(1): e20160087. [DOI:10.1542/peds.2016-0087] [PMID]

23. Meraj M, Singh S, Johri P, Quasim MT, editors. An investigation on infectious disease patterns using Internet of Things (IoT). 2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE);IEEE. 2020. [DOI:10.1109/ICSTCEE49637.2020.9276922]

24. Smith KP, Wang H, Durant TJ, Mathison BA, Sharp SE, Kirby JE, et al. Applications of artificial intelligence in clinical microbiology diagnostic testing. Clin Microbiol Newsl. 2020;42(8):61-70. [DOI:10.1016/j.clinmicnews.2020.03.006]

25. Patel SJ, Chamberlain DB, Chamberlain JM. A machine learning approach to predicting need for hospitalization for pediatric asthma exacerbation at the time of emergency department triage. Acad Emerg Med.2018;25(12):1463-70. [DOI:10.1111/acem.13655] [PMID]

26. Miller MB, Atrzadeh F, Burnham C-AD, Cavalieri S, Dunn J, Jones S, et al. Clinical utility of advanced microbiology testing tools. J Clin Microbiol. 2019; 57(9):10-11282. [DOI:10.1128/JCM.00495-19] [PMID] [PMCID]

27. Salazar BM, Balczewski EA, Ung CY, Zhu S. Neuroblastoma, a paradigm for big data science in pediatric oncology. Int J Mol Sci. 2016;18(1):37. [DOI:10.3390/ijms18010037] [PMID] [PMCID]

28. Hamet P, Tremblay J. Artificial intelligence in medicine. Metabolism. 2017;69:S36-S40. [DOI:10.1016/j.metabol.2017.01.011] [PMID]

29. Abdi J, Al-Hindawi A, Ng T, Vizcaychipi MP. Scoping review on the use of socially assistive robot technology in elderly care. BMJ Open. 2018;8(2): e018815. [DOI:10.1136/bmjopen-2017-018815] [PMID] [PMCID]

30. Murphy M, Killen C, Burnham R, Sarvari F, Wu K, Brown N. Artificial intelligence accurately identifies total hip arthroplasty implants: a tool for revision surgery. Hip Int. 2022;32(6):766-70. [DOI:10.1177/1120700020987526] [PMID]

31. Samorani M, Blount LG. Machine learning and medical appointment scheduling: creating and perpetuating inequalities in access to health care. Am J Public Health. 2020;110(4):440-1. [DOI:10.2105/AJPH.2020.305570] [PMID] [PMCID]

32. Bhandari M, Zeffiro T, Reddiboina M. Artificial intelligence and robotic surgery: current perspective and future directions. Curr Opin Urol. 2020;30(1):48-54. [DOI:10.1097/MOU.0000000000000692] [PMID]

33. Lonner JH, Zangrilli J, Saini S. Emerging Robotic Technologies and Innovations for Hospital Process Improvement. In: Lonner, J. (eds) Robotics in Knee and Hip Arthroplasty. Springer, Cham: London, U.K.; 2019. pp. 233-43. [DOI:10.1007/978-3-030-16593-2_23]

34. Huang S, Yang J, Fong S, Zhao Q. Artificial intelligence in cancer diagnosis and prognosis: Opportunities and challenges. Cancer Lett. 2020; 471:61-71. [DOI:10.1016/j.canlet.2019.12.007] [PMID]

35. Prados-Privado M, García Villalón J, Martínez-Martínez CH, Ivorra C, Prados-Frutos JC. Dental caries diagnosis and detection using neural networks: a systematic review. J Clin Med. 2020; 9(11):3579. [DOI:10.3390/jcm9113579] [PMID] [PMCID]

36. Orhan K, Bayrakdar I, Ezhov M, Kravtsov A, Özyürek T. Evaluation of artificial intelligence for detecting periapical pathosis on cone-beam computed tomography scans. Int Endod J. 2020;53(5):680-9. [DOI:10.1111/iej.13265] [PMID]

37. Johari M, Esmaeili F, Andalib A, Garjani S, Saberkari H. Detection of vertical root fractures in intact and endodontically treated premolar teeth by designing a probabilistic neural network: an ex vivo study. Dentomaxillofac Radiol. 2017;46(2): 20160107. [DOI:10.1259/dmfr.20160107] [PMID] [PMCID]

38. Crippa A, Salvatore C, Perego P, Forti S, Nobile M, Molteni M, et al. Use of machine learning to identify children with autism and their motor abnormalities. J Autism Dev Disord. 2015;45:2146-56. [DOI:10.1007/s10803-015-2379-8] [PMID]

39. Shu L-Q, Sun Y-K, Tan L-H, Shu Q, Chang AC. Application of artificial intelligence in pediatrics: past, present and future. World J Clin Pediatr. 2019;15(2):105-8. [PMID] [DOI:10.1007/s12519-019-00255-1]

40. Middleton B, Sittig D, Wright A. Clinical decision support: a 25 year retrospective and a 25 year vision. Yearb Med Inform. 2016;25(S 01):S103-S16. [DOI:10.15265/IYS-2016-s034] [PMID] [PMCID]

41. Chumbita M, Cillóniz C, Puerta-Alcalde P, Moreno-García E, Sanjuan G, Garcia-Pouton N, et al. Can artificial intelligence improve the management of pneumonia. J Clin Med. 2020;9(1):248. [DOI:10.3390/jcm9010248] [PMID] [PMCID]

42. Schmidt-Erfurth U, Bogunovic H, Sadeghipour A, Schlegl T, Langs G, Gerendas BS, et al. Machine learning to analyze the prognostic value of current imaging biomarkers in neovascular age-related macular degeneration. Ophthalmol Retina. 2018; 2(1):24-30. [DOI:10.1016/j.oret.2017.03.015] [PMID]

43. Nicholson C. Artificial Intelligence (AI) vs. Machine Learning vs. Deep Learning. Skymind, https://skymind ai/wiki/ai-vs-machine-learning-vs-deep-learning, printed Oct. 2019;9:6.

44. Asada K, Kaneko S, Takasawa K, Machino H, Takahashi S, Shinkai N, et al. Integrated analysis of whole genome and epigenome data using machine learning technology: Toward the establishment of precision oncology. Front Oncol. 2021;11:66:6937. [DOI:10.3389/fonc.2021.666937] [PMID] [PMCID]

45. Yasutomi S, Arakaki T, Matsuoka R, Sakai A, Komatsu R, Shozu K, et al. Shadow estimation for ultrasound images using auto-encoding structures and synthetic shadows. Appl Sci. 2021;11(3):1127. [DOI:10.3390/app11031127]

46. Hamamoto R, Suvarna K, Yamada M, Kobayashi K, Shinkai N, Miyake M, et al. Application of artificial intelligence technology in oncology: Towards the establishment of precision medicine. Cancers. 2020;12(2):3532. [DOI:10.3390/cancers12123532] [PMID] [PMCID]

47. Leo S, Cherkaoui A, Renzi G, Schrenzel J. Mini review: clinical routine microbiology in the era of automation and digital health. Front Cell Infect. 2020;10:582028. [PMID] [PMCID] [DOI:10.3389/fcimb.2020.582028]

48. Ruppé E, Schrenzel J. Messages from the second international conference on clinical metagenomics (ICCMg2). Microbes Infect. 2018;20(4):222-7. [DOI:10.1016/j.micinf.2018.02.005] [PMID]

49. Kanaujia R, Biswal M, Angrup A, Ray P. Inhale, then exhale: start afresh to diagnose Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) by non-invasive face-mask sampling technique. Clin Microbiol Infect. 2020;26(12):1701-2. [DOI:10.1016/j.cmi.2020.06.034] [PMID] [PMCID]

50. Rafeeq H, Zia MA, Hussain A, Safdar A, Bilal M, Iqbal HM. Role of Streptokinase as a Thrombolytic Agent for Medical Applications. In Industrial Applications of Microbial Enzymes. 1st Ed. CRC Press: Florida, U.S.; 2022. pp. 271-93. [DOI:10.1201/9781003202998-14]

51. Mahmoudi H, Moradi MH. The Progress and Future of Artificial Intelligence in Nursing Care: A Review. Open Public Health. 2024;17(1): E18749445304699. [DOI:10.2174/0118749445304699240416074458]

52. Tran NK, Howard T, Walsh R, Pepper J, Loegering J, Phinney B, et al. Novel application of automated machine learning with MALDI-TOF-MS for rapid

high-throughput screening of COVID-19: A proof of concept. Sci Rep.2021;11(1):8219. [PMID] [PMCID] [DOI:10.1038/s41598-021-87463-w]

53. Bibin D, Nair MS, Punitha P. Malaria parasite detection from peripheral blood smear images using deep belief networks. IEEE Access. 2017;5: 9099-108. [DOI:10.1109/ACCESS.2017.2705642]

54. Mathison BA, Kohan JL, Walker JF, Smith RB, Ardon O, Couturier MR. Detection of intestinal protozoa in trichrome-stained stool specimens by use of a deep convolutional neural network. J Clin Microbiol. 2020;58(6):10-128. [DOI:10.1128/JCM.02053-19] [PMID] [PMCID]

55. Tice AM, Farag HA. Machine learning in microbiology: Finding the signal in the noise. Clin Microbiol Newsl. 2019;41(14):121-7. [DOI:10.1016/j.clinmicnews.2019.06.004]

56. Haataja K, Gao X-Z, Toivanen P. Investigating drug peddling in Nigeria using a machine learning approach. In Intelligent Systems Design and Applicafions: 21st Internafional Conference on Intelligent Systems Design and Applicafions (ISDA 2021) Held During December 13; Vol. 15, No. 2021, Springer Nature: Berlin, Germany; 2022.

57. Frøssing L, Hartvig Lindkaer Jensen T, Østrup Nielsen J, Hvidtfeldt M, Silberbrandt A, Parker D, et al. Automated cell differential count in sputum is feasible and comparable to manual cell count in identifying eosinophilia. J Asthma. 2022;59(3):552-60. [DOI:10.1080/02770903.2020.1868498] [PMID]

58. Savardi M, Ferrari A, Signoroni A. Automatic hemolysis identification on aligned dual-lighting images of cultured blood agar plates. Comput Methods Programs Biomed. 2018;156:13-24. [DOI:10.1016/j.cmpb.2017.12.017] [PMID]

59. Smith KP, Kang AD, Kirby JE. Automated interpretation of blood culture gram stains by use of a deep convolutional neural network. J Clin Microbiol. 2018;56(3):10-128. [DOI:10.1128/JCM.01521-17] [PMID] [PMCID]

60. Henry KE, Hager DN, Pronovost PJ, Saria S. A targeted real-time early warning score (TREWScore) for septic shock. Sci Transl Med. 2015;7(299):299ra122. [DOI:10.1126/scitranslmed.aab3719] [PMID]

61. Kaushal V, Gupta R. Role of Artificial Intelligence in Diagnosis of Infectious Diseases. In Biomedical Translational Research: Technologies for Improving Healthcare. Springer Nature Singapore: Singapore; 2022. pp. 115-133. [DOI:10.1007/978-981-16-4345-3_8]

62. Mala R, Sood S, Kapil A, Gupta S, Singh N. Comparison of Amsel's criteria with low and high Nugent's scores for the diagnosis of bacterial vaginosis. Indian J Sex Transm Dis AIDS. 2022; 43(1):56-8. [DOI:10.4103/ijstd.ijstd_67_21] [PMID] [PMCID]

63. Fanelli U, Chiné V, Pappalardo M, Gismondi P, Esposito S. Improving the quality of hospital antibiotic use: Impact on multidrug-resistant bacterial infections in children. Front pharmacol. 2020;11:745. [DOI:10.3389/fphar.2020.00745] [PMID] [PMCID]

64. Smith KP, Kirby JE. Image analysis and artificial intelligence in infectious disease diagnostics. Clin Microbiol Infect. 2020;26(10):1318-23. [DOI:10.1016/j.cmi.2020.03.012] [PMID] [PMCID]

65. Cho SI, Han B, Hur K, Mun JH. Perceptions and attitudes of medical students regarding artificial intelligence in dermatology. J Eur Acad Dermatol Venereol. 2021;35(1):e72-e73. [DOI:10.1111/jdv.16812]

66. Madeleine M, Patel N, Plasmeijer E, Engels E, Bouwes Bavinck J, Toland A, et al. Epidemiology of keratinocyte carcinomas after organ transplantation. Br J Dermatol. 2017;177(5):1208-16. [DOI:10.1111/bjd.15931] [PMID]

67. Gomolin A, Netchiporouk E, Gniadecki R, Litvinov IV. Artificial intelligence applications in dermatology: where do we stand?. Front Med. 2020;7:100. [DOI:10.3389/fmed.2020.00100] [PMID] [PMCID]

68. Scull WR, Perkins MA, Carrier JW, Barber M. Community college institutional researchers' knowledge, experience, and perceptions of machine learning. Community Coll J Res Pract. 2023;47(5):354-68. [DOI:10.1080/10668926.2022.2043202]

69. Lim SS, Ohn J, Mun J-H. Diagnosis of onychomycosis: from conventional techniques and dermoscopy to artificial intelligence. Front Med. 2021;8:637216. [DOI:10.3389/fmed.2021.637216] [PMID] [PMCID]

70. Picek L, Šulc M, Matas J, Heilmann-Clausen J, Jeppesen TS, Lind E. Automatic fungi recognition: deep learning meets mycology. Sensors. 2022; 22(2):633. [DOI:10.3390/s22020633] [PMID] [PMCID]

71. Tahir MW, Zaidi NA, Rao AA, Blank R, Vellekoop MJ, Lang W. A fungus spores dataset and a convolutional neural network based approach for fungus detection. IEEE Trans Nanobioscience. 2018;17(3):281-90. [DOI:10.1109/TNB.2018.2839585] [PMID]

72. Van De Vooren J, Polder G, Van der Heijden G. Identification of mushroom cultivars using image analysis. Trans ASABE. 1992;35(1):347-50. [DOI:10.13031/2013.28610]
73. Zieliński B, Sroka-Oleksiak A, Rymarczyk D, Piekarczyk A, Brzychczy-Włoch M. Deep learning approach to describe and classify fungi microscopic images. PloS One. 2020;15(6): e0234806. [DOI:10.1371/journal.pone.0234806] [PMID] [PMCID]
74. Fricker M, Boddy L, Bebber D. Network organisation of mycelial fungi. In Biology of the fungal cell. Springer Berlin Heidelberg: Berlin, Germany. 2007. pp. 309-330. [DOI:10.1007/978-3-540-70618-2_13]
75. Zhang J, Lu S, Wang X, Du X, Ni G, Liu J, et al. Automatic identification of fungi in microscopic leucorrhea images. J Opt Soc Am A. 2017; 34(9):1484-9. [DOI:10.1364/JOSAA.34.001484] [PMID]
76. Santosh K, Ghosh S, GhoshRoy D. Deep learning for COVID-19 screening using chest x-rays in 2020: A systematic review. Int J Pattern Recognit Artif Intell. 2022;36(05):2252010. [DOI:10.1142/S0218001422520103]
77. Arora N, Banerjee AK, Narasu ML. The role of artificial intelligence in tackling COVID-19. Future Virol. 2020;15(11):717-24. [PMCID] [DOI:10.2217/fvl-2020-0130]
78. Gong H, Wang M, Zhang H, Elahe MF, Jin M. An explainable AI approach for the rapid diagnosis of COVID-19 using ensemble learning algorithms. Front Public Health. 2022;10:874455. [PMCID] [DOI:10.3389/fpubh.2022.874455] [PMID]
79. Ghosal A, Gupta N, Nandi E, Somolu H. Biomedical Data Driven COVID-19 Prediction Using Machine Learning Approach. In Artificial Intelligence and Machine Learning Methods in COVID-19 and Related Health Diseases. Cham, Springer International Publishing: Berlin, Germany. 2022. pp. 123-38. [DOI:10.1007/978-3-031-04597-4_6]
80. Huffman A, Ong E, Hur J, D'Mello A, Tettelin H, He Y. COVID-19 vaccine design using reverse and structural vaccinology, ontology-based literature mining and machine learning. Brief Bioinform. 2022;23(4):bbac190. [DOI:10.1093/bib/bbac190] [PMID] [PMCID]
81. David L, Brata AM, Mogosan C, Pop C, Czako Z, Muresan L, et al. Artificial Intelligence and Antibiotic Discovery. Antibiotics. 2021;10(11): 1376. [DOI:10.3390/antibiotics10111376] [PMID] [PMCID]
82. Kumar N, Kharkwal N, Kohli R, Choudhary S. Ethical aspects and future of artificial intelligence. In 2016 International Conference on Innovation and Challenges in Cyber Security (ICICCS-INBUSH). 2016 Feb 3 (pp. 111-114). IEEE: Greater Noida, India. 2016. pp. 111-4. [DOI:10.1109/ICICCS.2016.7542339]
83. Briganti G, Le Moine O. Artificial intelligence in medicine: today and tomorrow. Front Med. 2020; 7:509744.[DOI:10.3389/fmed.2020.00027] [PMID] [PMCID]