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Revolutionizing Medical Microbiology: The Role of Artificial Intelligence in Microbial Diagnostics and Research

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Abstract:

Conventional microbial diagnostics face challenges related to specimen handling, microbial isolation, result interpretation, and delays in antimicrobial resistance determination. The integration of artificial intelligence (AI), particularly machine learning (ML), offers efficient and innovative solutions to these limitations. This review emphasizes the importance of standardized sample processing and highlights recent advances in AI-based approaches for microbial classification, microorganism interaction analysis, and enhanced microscopy. Applications of convolutional neural networks in automated bacterial identification, digital pathology, colony counting, antimicrobial susceptibility testing, and disease surveillance are discussed, with examples including malaria, mycobacteria, and SARS-CoV-2. Despite ethical concerns regarding data privacy, integrity, and bias, AI-driven diagnostics demonstrate robust potential to transform diagnostic microbiology.

Key Words: AI, M.L., D.L., CNN

Introduction:

Laboratory diagnosis of pathogens is a critical component of healthcare, relying on techniques such as culture, molecular analysis, and to identify infectious agents. However, conventional diagnostic methods are often limited by challenges in antimicrobial susceptibility testing, sample handling, subjective interpretation.[1] Artificial intelligence (AI), specifically machine learning and deep learning, have significantly transformed microbiological diagnostics by enabling rapid and accurate analysis of complex datasets, including microbial phenotypes, clinical metadata, and genetic sequences. AI-driven tools facilitate optimized treatment strategies, early detection, improved patient outcomes while also addressing the growing challenge of antimicrobial resistance. [2] This review highlights the emerging role of AI in microbial diagnostics, discussing its advantages, applications, limitations in the context of recent technological advancements.

1. **Emerging Trends of AI and Machine Learning in Human Health**

Artificial intelligence (AI) enables personalized and accurate diagnosis, ensuring data security and improving access to medical technologies [3, 4]. AI tools such as ChatGPT are increasingly integrated into routine and clinical workflows, with approximately 500 companies adopting Generative Pre-trained Transformer–based systems, reflecting their reliability [5–7]. AI and machine learning (ML) models efficiently uncover relational patterns within disease-associated and complex biological datasets, including genomic and sequencing data. ML applies mathematical modeling to identify predictive patterns through trained learning, while deep learning (DL), using artificial neural networks (ANNs), enhances performance through layered data processing driven by high-quality datasets [8].

ML and DL aids in cancer diagnosis, prognosis, and personalized medicine [9]. In computational pathology, DL-based image analysis has improved lymph node metastasis detection [10], Ki67 scoring in breast cancer [11], Gleason grading in prostate cancer [12], and molecular marker prediction [13], increasing prognostic accuracy by 15–25% [14].

The integration of AI with the Internet of Medical Things (IoMT) enables intelligent point-of-care testing, robotic surgery, individualized therapeutic strategies [15–17].

AI applications are advancing microbial diagnostics via volatile organic compounds (VOC) profiling, antimicrobial resistance (AMR) prediction. ML-based analysis of (VOCs) in biological samples has revealed disease and pathogen-specific signatures [18–25,26–29].Moreover, ML-driven pan-genome approaches improve AMR prediction by identifying resistance-associated gene clusters and phenotypes [30,31].

2. The Impact of AI and Convolutional Neural Networks on the Diagnosis of Infectious Diseases

2.1 SARS –Cov-2

Deep learning (DL), particularly convolutional neural networks (CNNs), represents a recent advancement in artificial intelligence, through the multilayered structure of the human visual cortex and demonstrating strong capabilities in processing, image acquisition, and analysis [32]. Across biomedical applications, these attributes have positioned CNNs as powerful tools. During the SARS-CoV-2 pandemic, CNNs, other AI-based technologies were widely adopted for crucial tasks such as viral genome sequencing [33], development of vaccines [34], and drug discoveries [35].

In pathology laboratories, the AI-enabled digital pathology system has markedly improved the efficiency and accuracy of identifying microorganisms in cytological and histological specimens [36]. RT–PCR remains the gold standard for COVID-19 diagnosis through detection of SARS-CoV-2 [37], the revolutionary demand during the pandemic highlighted the need for faster and more reliable workflows. Several AI-assisted models were developed to enhance RT–PCR performance. Long short-term memory (LSTM) models have been applied to raw fluorescence data from RT–PCR cycles to reduce turnaround time [38]. Moreover, AI-based systems capable of fluorescence signals and automatically classifying amplification curves demonstrated improved diagnostic accuracy [39]. Machine learning (ML) models further enabled the identification of atypical RT–PCR curves associated with contamination or artifacts, reducing false-positive results [40]. ML and dense neural network (DNN) approaches have also been used to detect S.A.R.S.-CoV-2 variants based on cycle threshold (Ct) values and biosensor data [41, 42]. These AI tools played a crucial role in effective pandemic control, early detection, and patient isolation [43].

2.2 Malaria

Malaria remains a major global health burden, where accurate diagnosis is essential for effective treatment. Conventional diagnosis relies on light microscopy, peripheral blood smears, the gold standard, but is limited by dependency of an operator and difficulty in distinguishing life-cycle stages and Plasmodium species. Many, AI-based approaches—particularly CNNs such as VGG, YOLO, and ResNet—have been widely applied. These systems demonstrate robust performance and enable reliable estimation of parasitemia.
Advanced models, including mobile-based digital microscopy further enhance automated diagnosis in resource-limited settings [44–59].

2.3 Mycobacteria

Mycobacterial infections represent global health burden resulting in considerable morbidity and mortality. These infections predominantly affect individuals with predisposing conditions such as immunodeficiency and malnutrition [60]. Mycobacteria are broadly classified into two groups: *Mycobacterium tuberculosis* and atypical (nontuberculous) mycobacteria. These organisms are small, bacilli-shaped bacteria that pose diagnostic challenges, particularly when using conventional light microscopy and routine stains such as hematoxylin and eosin (H&E).

Although special staining techniques, including Ziehl–Neelsen and Auramine O stains, have improved visualization, manual detection of mycobacteria in clinical specimens remains labor-intensive and error-prone. A diagnosis of mycobacteriosis typically depends on the identification of at least one acid-fast bacillus (AFB).

Recent advancements focus on AFB detection using computer vision and digital imaging approaches. Artificial intelligence (AI)-based studies focuses on sputum cytology smears, several investigations have also applied CNNs) to histopathological samples, including lung biopsy specimens [61, 62]. Image-processing algorithms for AFB detection have shown notable improvements, particularly in sputum [63, 64]. Enhanced color discrimination, such as optimized red–green contrast, pixel-based color segmentation in advanced AI models, has contributed significantly to improved performance [65]. Furthermore, CNN-based whole-slide image (WSI) patch analysis has demonstrated superior diagnostic accuracy [66].

Overall, advances in digital imaging and CNN-based analysis provide opportunities for the automated detection.

3. Artificial Intelligence–Driven Transformation of Diagnostic Microbiology

AI has transformed pathology by automating the recognition of cytological and morphological patterns associated with infections.

3.1 Revolution in Colony Counting

Colony counting by Manual method is prone to human error [67]. Recent advancement in machine learning (ML)–based image analysis enables high-resolution visual assessment systems with improved sensitivity, allowing detection of small colonies. AI-driven colony counting system requires standardized results while accounting for critical colony features such as size, shape, contrast [68]. Abilities include accurate colony segmentation, particularly for aggregated colonies, high-quality image acquisition and resolution, rapid processing (≤1 s per plate), and visualization under both white light and fluorescence [69]. Additional functional requirements include differentiation of chromatic and achromatic images, whole-plate or sector-based counting, real-time full-color display with zoom capability, and seamless data integration with laboratory information management systems (LIMS) [70].

In automated workflows, FDA-cleared platforms such as APAS Independence distinguish negative urine cultures from growth exceeding predefined thresholds and support screening for methicillin-resistant *Staphylococcus aureus* (MRSA) [71]. Similarly, PhenoMatrix (bioMérieux) demonstrates aboutidentifying *Streptococcus pyogenes,Streptococcus agalactiae* (group B streptococcus) [72]. Becton Dickinson Kiestra, developed deep convolutional neural network (CNN)–based systems for automated urine culture image analysis [73].

Image analysis systems serves as rapid screening tools for differentiating positive and negative cultures, enabling early exclusion of plates with no growth or normal flora contamination and reducing manual workload [74,75]. Accurate assessment of contamination remains a major challenge for AI systems due to transport, clinical context specimen, variability, transport and processing conditions and the need for expert microbiological judgment [76]. ML-based colony counting continues to advance, persistent challenges—including low image resolution, high CFU density, background noise, plate boundary artifacts, and edge-located colonies—are being addressed through optimization [77].

3.2Advancements in AI Applications for Antimicrobial Susceptibility Testing

Recent advances illustrate the critical role of artificial intelligence (AI) in antimicrobial susceptibility testing [78]. AI algorithms have shown effectiveness in detecting aminoglycoside resistance in *Staphylococcus aureus and Escherichia coli*, while computer vision–based culture screening enables early identification of resistant pathogens (MRSA and VRE) [79,80]. Integration of AI with total laboratory automation systems, (Kiestra TLA and WASPLab) is increasingly adopted in skilled laboratories [81]. Furthermore, MALDI-TOF MS with machine learning has extended its application from microbial identification to antimicrobial resistance prediction, achieving sensitivities up to 92.3% in *Campylobacter* species [80].

3.3 AI-Enhanced Microscopes for Automated Microbial Classification

Microscopes integrated with AI exhibit potential in examination of organisms and leveraging data in diagnosis and root cause analysis. An earlier study showed the efficacy of an automated AI-enhanced microscope in identifying bacterial images [68]. Machine intelligence acquired the capability to classify images into three distinct categories (rod-shaped, chains or pairs, clusters). Furthermore, the system's ability for remote transmission of images to microbiologists on global scale enhances accessibility [68]

Conclusion:

Artificial intelligence has enhanced microbial diagnostics by improving the efficiency, speed, accuracy of pathogen detection and antimicrobial resistance analysis when integrated with conventional methods. Despite its transformative potential for public health and clinical care, challenges related to bias, ethics, data quality, bias, equitable access must be addressed through robust validation and regulatory oversight.

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