Review

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AI-Powered Diagnosis: A New Weapon Against Cancer and Microbial Infections

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Review

AI-Powered Diagnosis: A New Weapon Against Cancer and Microbial Infections

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Abstract: Artificial Intelligence (AI) has emerged as a transformative tool in computational biology, enabling unprecedented advancements in medical diagnostics and research. AI efficiently processes and analyzes large, complex datasets, uncovering intricate patterns in genomics, proteomics, and clinical records. This review explores the applications of AI in diagnosing bacterial infections and cancer, highlighting its potential to revolutionize personalized medicine. Breakthroughs such as AlphaFold in structural biology, AI-driven drug discovery, and enhanced imaging techniques underscore AI's impact on healthcare. AI has advanced microbial diagnostics, enabling rapid identification and characterization of pathogens, antimicrobial resistance genes, and disease markers. Similarly, in oncology, AI tools excel in early cancer detection, prognosis prediction, and patient stratification, improving outcomes and reducing mortality rates. However, challenges such as bias in datasets, lack of interpretability, and integration hurdles within clinical workflows persist. This article reviews current advancements, clinical applications, and limitations of AI in medical diagnostics, offering insights into future directions for its development and integration into healthcare systems. Addressing these challenges will be crucial to maximizing AI's potential to enhance diagnostic accuracy, reduce disparities, and improve global health outcomes.

Keywords: artificial intelligence; machine learning; diagnosis; cancer; bacterial infection; convolutional neural network; artificial neural network; support vector machine; deep learning

1. Introduction

Artificial Intelligence (AI) has become a transformative force in computational biology, revolutionizing how we analyze, interpret, and utilize biological data. It excels at managing the vast, complex datasets generated by modern biological research, enabling the discovery of intricate patterns and relationships (Han et al., 2022). Artificial Intelligence (AI) refers to the simulation of human cognitive processes using machines, enabling them to think, learn, and make decisions. It includes technologies like computer vision, machine learning, and natural language processing that let machines do things like recognize patterns, solve problems, and make decisions. It has broad spectrum applications and is continuously applied in biology, psychology, sociology, mathematics, computer science, neuron study and statistics. AI provides precise results and can perform the same task multiple times with high accuracy (Foreman et al., 2018). Machine learning (ML) in artificial neural networks (ANN) is one of one of the most exciting AI advancements in medicine; inspired by the structure and function of biological neural networks in the human brain. They consist of layers of interconnected nodes, or "neurons," which process data through weighted connections. (Sung et al., 2021).

AI plays a crucial role in genomics, it identifies genetic variants and elucidating gene expression, while its applications in drug discovery accelerate target identification, virtual screening, and personalized medicine (Klambauer et al., 2019). Breakthroughs like AlphaFold have demonstrated AI's power in predicting protein structures with near-experimental accuracy, facilitating deeper

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insights into molecular mechanisms (Pak et al., 2023). In epidemiology, AI aids in predicting disease outbreaks, optimizing vaccine development, and modeling the spread of infectious diseases (Parums et al., 2023). It has also transformed biological imaging, automating image analysis for diagnostics and research, and contributed to systems biology by modeling complex cellular networks and pathways. AI also enhances ecological and evolutionary studies through species classification and phylogenetic analysis (Devenport et al., 2019). In genomics, tools like DeepVariant have significantly improved genome annotation and variant detection, enhancing our understanding of gene regulation and expression (Chen et al., 2022). AI has also reshaped drug discovery, with the first AI-designed drug entering clinical trials in 2020 and rapid drug repurposing efforts during the COVID-19 pandemic. In diagnostics, AI systems like PathAI have achieved exceptional accuracy in detecting cancer and rare diseases, while tools like CellProfiler have automated cell imaging and phenotype classification. AI has played a critical role in epidemiology and vaccine development, from modeling disease outbreaks to accelerating the design of COVID-19 vaccines (Ochoa et al., 2022). In microbiome research, AI has enhanced the analysis of microbial communities, and in ecological studies, it has enabled species classification and accelerated phylogenetic analysis (Ma et al., 2023). AI-powered personalized medicine now predicts patient-specific treatment outcomes, guiding precision oncology and other therapeutic strategies. Additionally, AI has advanced systems biology by modeling complex networks, uncovering key interactions, and facilitating synthetic biology innovations (Wang et al., 2022).

In healthcare, for instance, AI systems can quickly analyze medical images to detect early signs of diseases, aiding in faster and more accurate diagnoses (Li et al., 2020; Anooj et al., 2012; Mariani et al., 2019) (Table 1). AI systems are designed to learn from data and experience. Instead of being programmed to perform one specific task, many AI systems use data to identify patterns, make predictions, and adjust their behavior to improve over time. By recognizing patterns in images, AI can classify objects, detect abnormalities, and even track movements. AI can be programmed to make decisions, often by using **expert systems** that simulate human decision-making in specialized areas, like diagnosing medical conditions or financial planning. These systems can make decisions and suggestions based on data or by adhering to preset criteria.

The increase in mortality rates due to microbial pathogen infections has become a global health concern (Nabadda et al., 2020,). Bacteria have the potential to cause infections in both humans and animals through a variety of means, such as exposure to bodily fluids (including blood, saliva, or mucus), contact with contaminated surfaces, proximity to infected individuals, consumption of contaminated food, and ingestion of contaminated water (De et al., 2012). Bacteria have been found in tumors for a long time, with over 16% of cancer cases linked to infectious agents (Rabaan et al., 2023), and intratumor bacteria identified in various types of tumors (Peters et al., 2019; Ma et al., 2018).

Cancer is a leading cause of death and a major obstacle to increasing life expectancy. Global projections suggest that the impact of cancer will continue to grow over the next two decades, significantly adding to the overall burden of disease. (Jiang et al., 2017; Xiong et al., 2018). By using massive data sets, technological developments in AI and ML have cleared the way for autonomous illness diagnosis systems that will address future issues for early human disease detection, particularly in cancer (Lin et al., 2023).

Table 1. AI modules used for diagnostics.

Main AI Module	Specified Algorithm	Used for	Specificity	Features & outcomes	Reference
Supervised learning	COVNet based on ResNet-50	Detection of COVID-19	96%	X-ray image of COVID-19 patients & can distinguish between pneumonia and	Li et al., 2020

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				COVID-19 patients.	
	Clinical decision support system (CDSS) by using Weighted Fuzzy Rules	Predicting heart disease	62.35%	Age, sex, total cholesterol level, HDL, LDL, age, smoking status, hypertension, and pre-eclampsia that are mainly used to predict the risk level	Anooj, P.K., 2012
	Logistic regression	Predicting breast cancer	98.94%	Prediction based on cell size	Miriani et al., 2019
	Logistic regression	Predicting and diagnosing prostate cancer	90.6%	Multiparametric magnetic resonance imaging (mp-MRI)	Nematollahi et al., 2023
Unsupervised learning	k- nearest neighbor (k- NN)	Diagnosis of endometriosis	89.7%	Detection using Raman spectroscopy	Parlatan et al., 2019
	RF with leave One Cut Out Cross Validation (LOOCV)	Diagnosing lung cancer	96.7%	Analyzing saliva sample using Raman spectroscopy	Qian et al., 2018
	k-NN, RF	Identification of carbapenem resistant vs. sensitive *K. pneumoniae*	93%	Use MALDI TOF-MS technique	Huang et al., 2020
	SVM, k-NN	Detection of *Plasmodium* species	99.5%, 99.1%	Microscopic examination of blood smears	Brozan et al., 2008
	Random forest (RF), SVM,	Detection of Tuberculosis bacteria	-	Detection of *M. tuberculosis* using fluorescent microscopic and features extraction techniques.	Zheng et al., 2016
Reinforced learning	Q- learning	Detection of melanoma	61.4%-79.5%	Image analysis of skin lesions	Barata et al., 2023
	Deep-Q-network (DQN)	Identify active breast lesions	-	Use dynamic contrast-enhanced magnetic resonance imaging	Miacas et al., 2017
	RL-CancerNet based on Q-network	Detect cervical cancer	99.32%	Cell images from Pap smear	Muksimova et al., 2024

With an emphasis on its revolutionary influence on medical diagnostics, this review article will examine the developments in AI for the diagnosis of cancer and bacterial infections. We will examine the role of AI in clinical trials across diverse diseases and medical conditions, delve into its current limitations, and discuss potential future directions for this rapidly evolving field. Additionally, the

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article will address ethical considerations, integration challenges in healthcare systems, and the potential of AI to revolutionize personalized medicine and early disease detection.

1.1. Algorithms and Packages in Diagnostics

AI algorithms are pivotal in enabling machine to learn, analyze data, and make decisions autonomously. Main types of AI algorithms are; supervised learning algorithm, unsupervised learning algorithms, reinforced learning algorithms. Supervised learning algorithms are trained on annotated datasets to predict specific clinical outcomes in which the input data is linked to the appropriate output. The objective is to teach the model to map inputs to outputs using the labelled examples so that it can accurately predict new, unknown data (Li, 2023). Unsupervised learning algorithm learns from an unlabeled data set by identifying patterns, correlations or clusters within the data (Hansson et al., 2023). Reinforced learning (RL) algorithm learns by interacting with an environment, receiving feedback in the form of rewards or penalties. RL is an advanced approach where a model learns to optimize its actions through trial and error by interacting with its environment. (Amin et al., 2024).

In medical diagnostics, supervised learning algorithms are essential for analysing and interpreting medical data. These algorithms are trained on labeled datasets, such as patient records, imaging scans, or laboratory results, to identify patterns and make predictions, such as diagnosing diseases, predicting outcomes, or recommending treatments. They improve the precision and effectiveness of diagnostic procedures by learning from past data, facilitating better clinical decision-making (Brasen et al., 2024).

2. AI in Diagnosis of Bacterial Infections

AI, ML and deep learning (DL) have significantly advanced the automatic recognition and classification of pathogenic microorganisms in microscope images. These technologies excel in detecting bacteria, viruses, fungi, and parasites with remarkable accuracy, surpassing traditional culturing techniques that often take days to yield results (Table 2). DL, in particular, has revolutionized microscope image analysis by enabling precise cell detection and classification, greatly enhancing diagnostic speed and reliability (Esteva et al., 2021; Chen and Asch, 2017).

A study carried out by (Wang et al., 2020) introduced a high-throughput platform that rapidly detects and classifies bacterial colonies on chromogenic media, focusing on *E. coli*, *K. aerogenes*, and *K. pneumoniae*. The system successfully detected bacterial growth within 3 hours, identified 90% of colonies in 7–10 hours, and over 95% in 12 hours, with a precision of 99.2–100%. This innovation cut traditional analysis time by more than half. The platform is powered by MATLAB, Python/PyTorch, and C/C++ which achieved detection sensitivity as low as 1 colony-forming unit (CFU) per 100–1000 mL in under 12 hours using a Pseudo-3D DenseNet and a DNN-based detection model.

Building on these advancements in AI-driven bacterial detection, (Kim et al., 2023) introduced another groundbreaking approach by integrating super-resolution fluorescence imaging with AI for single-cell bacterial identification. Unlike traditional colony-based detection, this method focuses on analyzing bacteria at the single-cell level, offering even greater diagnostic precision. Their AI algorithms, including EfficientNetV2-S, SwinV2-S, and SwinV2-T, were used for protein quantification and image analysis. When tested on *S. aureus*, *S. epidermidis*, and *C. acnes*, this approach achieved 100% accuracy, successfully distinguishing different bacterial species based on protein distribution and quantity. These innovations further demonstrate how AI is reshaping microbial diagnostics, enabling faster and more accurate pathogen identification than ever before.

Table 2. AI algorithms for the detection of bacterial infections.

Diseases	Algorithm	Specificity	Outcomes/ Results	References
Meningitis	Decision trees	80%	Can predict presence of meningitis based on the	Lelis et. al., 2020

			symptoms, chemical & cytological analysis and etiological origin	
	BBN	99.99%	For early diagnosis of meningitis	Alile et. al., 2020
Viral and bacterial pneumonia	DNN	95.7% & 100%	Can detect viral, bacterial and COVID-19 infections	Ozsoz et. al., 2020
Tuberculosis	DL & ML	83.65%	Automatic detection of TB bacilli	Xiong et. al., 2018
Helicobacter pylori infection	CNN & scSE-CatBoost	81%	Can detect the infection with 100% sensitivity	Lin et. al., 2023
Acne vulgaris	EfficientNetV2-S, SwinV2-S, and SwinV2-T	100%	For single-cell bacterial identification	Kim et al., 2023
Spontaneous bacterial peritonitis (SBP)	Decision trees & RF	100%	Measures the differences in ascitic fluid composition of SBP and non-SBP patients	Khorsand et al., 2025

Beyond bacterial identification, Significant progress has also been made by AI in the diagnosis of infectious diseases brought on by different pathogens (Xiong et al., 2018) developed an efficient framework for the automatic detection of *Mycobacterium tuberculosis* (TB) bacilli using DL and ML algorithms. The system, TB-AI, analyzes smear images scanned by a digital section scanner to identify acid-fast bacilli. Demonstrating high sensitivity (97.94%) and specificity (83.65%) in bacilli recognition, TB-AI provides a reliable and automated solution for tuberculosis diagnosis.

Further expanding AI's role in clinical diagnostics, (Lin et al., 2023) introduced a novel AI classification system to detect *Helicobacter pylori* infection from white-light endoscopic images of peptic ulcers and gastric cancer. By integrating convolutional neural networks (CNN) with scSE-CatBoost model, their system achieved 100% sensitivity, 81% specificity, and 90% accuracy. This non-invasive, high-accuracy alternative to traditional biopsy-based diagnostics not only reduces costs and time but also enhances early detection and treatment strategies

In addition to microbial diagnostics, AI has been increasingly applied to clinical decision-making, particularly in life-threatening conditions such as meningitis, pneumonia, and cystic fibrosis. Lelis et al., (2020) developed an open, integrated Clinical Decision Support System (CDSS) designed for the early diagnosis of meningitis. The system, which leverages decision trees and expert knowledge of symptoms, significantly improved the diagnosis of severe meningitis and could predict its presence even before hospitalization or invasive testing. The tree-based models demonstrated strong predictive power, with ROC area values exceeding 80%, while also providing interpretability regarding how input features influenced predictions. Similarly, (Alile et al., 2020) employed a Bayesian Belief Network (BBN)-based AI model for the early diagnosis of meningococcal meningitis, from its symptoms and serogroup types. Their model achieved an astonishing 99.99% accuracy in disease prediction, suggesting better outcomes than the prior study, further highlighting AI's potential in high-stakes clinical settings

AI models have also demonstrated strong utility in respiratory disease diagnostics, particularly in distinguishing different types of pneumonia. Ozsoz et al., (2020) proposed a DNN using transfer learning, specifically the pretrained AlexNet model, for the automatic detection of pneumonia types, including COVID-19 associated pneumonia, non-COVID-19 viral pneumonia, and bacterial pneumonia (Figure 5). The model generated predictions using images obtained from various platforms, including GitHub and Kaggle. The dataset comprised 2,882 normal images, 4,078 bacterial pneumonia cases, 4,237 non-COVID-19 viral pneumonia cases, and 371 COVID-19 pneumonia cases.

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The model delivered exceptional results, achieving 99.16% accuracy for COVID-19 pneumonia, 91.43% accuracy for bacterial pneumonia, and 94.43% accuracy for non-COVID-19 viral pneumonia. The exceptional specificity and sensitivity i.e., 100% specificity in bacterial pneumonia detection and a high sensitivity of 97.44% for COVID-19 pneumonia. These developments show how important AI is to pandemic-related diagnostics, enabling quicker and more precise detection of respiratory illnesses, which eventually improves patient outcomes and the distribution of resources in medical facilities.

Together, these breakthroughs highlight AI's profound impact across multiple domains of microbial and clinical diagnostics. From colony-based bacterial identification to single-cell imaging, AI-powered pathogen detection, decision-support systems, these innovations are revolutionizing diagnostics, improving treatment strategies, and accelerating drug discovery. As AI continues to evolve, its potential to enhance diagnostic precision, reduce costs, and facilitate early disease detection remains unparalleled, positioning it as a game-changer in modern healthcare.

2.1. AI in Diagnosis of Viral, Fungal & Parasitic Infections

AI has emerged as a powerful tool in detecting a wide range of infections, including viral, fungal, and parasitic diseases, offering greater accuracy and speed compared to conventional diagnostic techniques (Table 3). For instance, (Mei et al., 2020) developed a joint convolutional neural network (CNN) model that integrated radiological and clinical data for the rapid diagnosis of COVID-19, outperforming traditional RT-PCR testing in speed. Their approach utilized DL and ML techniques, including CNN, support vector machines (SVM), multilayer perceptron (MLP), and random forest classifiers. The CNN-based AI model analyzed chest scans using a pretrained Inception-ResNet-v2 model, which was trained on ImageNet and employed as a slice selection CNN to identify abnormal CT images (Figure 1: https://www.nature.com/articles/s41591-020-0931-3/figures/3). Meanwhile, ML models classified cases based on clinical data such as patient age, sex, exposure history, symptoms, and complete blood count (CBC). This integrated AI model achieved an impressive 95% specificity, sensitivity, and accuracy, demonstrating its potential for fast and reliable COVID-19 diagnosis.

AI has also been instrumental in identifying other viral threats, such as monkeypox, which has seen a tenfold increase in cases over the past five decades. AI-driven detection enables the rapid and precise differentiation of monkeypox skin lesions from those of similar diseases like chickenpox and measles. Sorayaie et al., (2023) developed seven modified DL models for diagnosing monkeypox, with DenseNet201 proving to be the most effective. Utilizing advanced interpretability techniques like Local Interpretable Model-Agnostic Explanations (LIME) and Gradient-weighted Class Activation Mapping (Grad-CAM), the model efficiently analyzes images, accurately distinguishing monkeypox lesions from other pox-related diseases.

Kawamoto et al., (2024) introduced a novel machine learning-based approach for detecting Respiratory Syncytial Virus (RSV). The study evaluated three machine learning algorithms—Random Forest (RF), XGBoost, and Support Vector Machine (SVM)—to identify the most effective model. The dataset comprised patient symptoms and RSV rapid antigen test results obtained using the Quick-Navi RSV test in children under 24 months of age. Hyperparameter tuning was conducted via grid search within a defined parameter space, using 10-fold cross-validation. Among the tested models, XGBoost achieved the highest accuracy of 95% and was selected for both the proposed and baseline models. In paediatric patients, the model demonstrated a sensitivity of 68% and a specificity of 73.2%.

Table 3. AI algorithms used for the detection of viral, parasitic and fungal infections.

Disease	Algorithm	Accuracy	Outcome/results	References
COVID-19 disease	Inception-ResNet-v2 model	95%	Can diagnose disease based on image analysis along with patient's clinical data/reports	Mei et al.,2020

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Monkeypox	DenseNet201 along with LIME & Grad-CAM	97.63%	Can accurately diagnose and distinguish monkeypox lesions from other pox disease	Sorayaie et al., 2023
RSV	XGBoost	95%	Can remotely confirm RSV infection based on patient reported symptoms and rapid antigen test results	Kawamoto et al., 2024
Ascaris lumbricoides, Schistosoma mansoni, Trichuris trichiura,	CNN	96.1%	Detection of parasites and their eggs from Kato-Katz stool thick smear slide images using WSI scanner	Ward et al., 2022
	AdaBoost	87%	Use microscopic images of fecal samples to detect and quantify parasites	Caetano et al., 2023
Candida spp.	KNN classifier, Time Series Forest classifier, and BOSS ensemble	100%	Can detect fungal pathogen through their metabolic byproducts using E-noses	Bastos et al., 2024
Vulvovaginal Candidiasis	R-CNN & YOLOv5s	89.3%	Image-based analysis of vaginal discharge slides for VVC prediction through detection and identification of various yeast morphological stages.	Wang et al., 2025

Parasitic infections remain a significant health challenge in developing countries due to inadequate sanitation and infrastructure, leading to widespread enteric diseases. Rapid and accurate diagnosis is crucial for effective treatment, and AI is transforming parasite detection by enhancing speed and accuracy.

In this effort, (Ward et al., 2022) developed an AI-powered digital pathology (AI-DP) device capable of identifying *Ascaris lumbricoides, Schistosoma mansoni, Trichuris trichiura,* and hookworm eggs from Kato-Katz stool thick smear slides. Utilizing a convolutional neural network (CNN)-based Whole Slide Imaging (WSI) scanner, the system successfully classified 1,605 out of 1,671 images, achieving an impressive 96.1% accuracy.

Building on this advancement, (Caetano et al., 2023) introduced an AI-driven detection software that leverages an AdaBoost classifier and an automated optical microscope to analyze microscopic images of fecal samples. This system accurately detected and quantified *Ascaris lumbricoides, Schistosoma mansoni, Enterobius vermicularis,* and *Trichuris trichiura,* achieving a global accuracy of 87%. These AI-powered diagnostic tools demonstrate significant potential in streamlining parasitic infection detection, making it faster, more precise, and more accessible, particularly in resource-limited settings.

AI has also been instrumental in identifying fungal pathogens from clinical isolates, drastically cutting down on the amount of time needed for diagnosis when compared to conventional cultivation techniques. While fungal cultures typically take days to grow, AI-powered detection can provide results within hours. Xu et al., (2023) developed a novel, rapid, and highly accurate diagnostic platform for identifying clinical fungal pathogens. They constructed a Raman database comprising 94 clinical fungal strains from various infection sources. This system detects fungal isolates based on their cell wall composition, measured using Raman spectroscopy. By employing a linear discriminative analysis (LDA) model for classification, the AI system achieved an outstanding 100% accuracy.

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AI-driven technologies have also been used to identify fungal diseases by their metabolic byproducts, in addition to analysing the composition of their cell walls. Bastos et al., (2024) explored the use of electronic noses (E-noses) combined with AI to identify *Candida* spp. Fungal strains were cultured on SDA and analyzed using an E-nose, which detects the "smell fingerprints" of fungi by measuring volatile organic compounds (VOCs). These VOCs were then classified using multiple machine learning algorithms, including the KNN classifier, Time Series Forest classifier, and BOSS ensemble, achieving an impressive 100% accuracy.

Wang et al., (2025) developed an AI-assisted diagnostic approach for vulvovaginal candidiasis (VVC) using a cascade neural network model. To construct the cascade model, the study utilized 1,761 vaginal discharge slides, from which 100,387 microscopic images were extracted from 599 slides to build an image-level object detection framework. The model identified VVC based on the morphological characteristics of yeast, employing both the R-CNN and YOLOv5s models to detect pathogenic microorganisms at the image level. The proposed model achieved sensitivities of 91.35% for yeast hyphae, 91.28% for budding yeast, 96.00% for yeast, and 84.98% for VVC. These advancements highlight AI's transformative potential in fungal diagnostics, offering rapid and highly precise identification through diverse analytical approaches.

2.2. AI in Diagnosis of Cancer

Early cancer diagnosis is crucial for improving patient prognosis and reducing cancer mortality rates. Detecting cancer in its initial stages not only enhances survival rates by enabling timely intervention but also spares patients from aggressive treatments like chemotherapy and radiation, which often come with severe side effects. Since early-stage cancers are generally more responsive to treatment, early detection significantly increases the chances of a favorable outcome (Foreman et al., 2016). Advances in AI are revolutionizing cancer diagnostics by offering rapid, precise, and cost-effective solutions across various malignancies. AI enhances detection by analyzing medical images, identifying subtle patterns undetectable to the human eye, and recognizing biomarkers in genetic and clinical data, enabling faster and more accurate diagnoses (Table 4).

One such advancement is the CHIEF (Clinical Histopathology Imaging Evaluation Foundation) model, developed by (Wang et al., 2024) for cancer diagnostics and prognostics. By analyzing 13,432 whole-slide images (WSIs) from 30 cancer types, this framework was able to identify tumor origins, predict genomic profiles, and stratify patients based on survival outcomes. The study focused on 53 highly mutated tumor-marker genes, selecting the top five for each cancer type, demonstrating AI's potential in uncovering critical biomarkers and guiding personalized treatment strategies.

Table 4. AI algorithms used for the detection of cancer.

Cancer type	Algorithm	Detection time & Specificity	Outcomes/ Results	References
Cancer diagnosis	ML & DL	sec to few min 95%	Can distinguished patients with longer-term survival from those with shorter-term survival, can predict mutation status of several oncogenes'	Wang et al.,2024
Skin cancer	QUADAS-2	few min 98%	can predict the invasiveness of the skin lesions	Chuchu et al., 2018
	CNN	few min 96.4%		Kränke et al. 2023
Prostate cancer	CNN	2 min 99.3%	for detection, grading, and quantification of **prostate cancer**	Eloy et al.,2023
Brain cancer	RNN	NA 90%	for the detection of brain tumors by analyzing clinical, genomic, and imaging data.	Vallathan et al., 2023

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Liver pathologies	YOLOv3	10 sec 99.5%	Automated, efficient, and reproducible image prescription for liver MRI scans.	Geng et al., 2023
Liver cancer	CNN	NA 98%	can predict malignant hepatic tumor and hemangiomas from abdominal MRI scans	Wu et al., 2023
Lung cancer	DenseNet201	NA 99.68%	lung cancer detection via color histograms	Noaman et. al., 2024
Chronic Lymphocytic Leukemia	CNN	seconds to minutes 95%	Can quantify cell morphologies and can distinguish them based on their morphology	Wang et al., 2023

Additionally, AI has advanced significantly in the identification of skin cancer, particularly for invasive cutaneous melanoma. The University of Birmingham developed a smartphone app designed for triaging adults with suspicious skin lesions (Figure 2: https://pmc.ncbi.nlm.nih.gov/articles/PMC6517294/figure/CD013192-fig-0001/), effectively ruling out invasive melanoma and atypical intraepidermal melanocytic variants (Chuchu et al., 2018). Building upon these efforts, (Kränke et al., 2023) introduced an AI-powered smartphone algorithm that leverages convolutional neural networks (CNN) and region proposal networks (RPN) to analyze skin lesions. The system classifies lesions as malignant, benign, or precancerous with a remarkable detection accuracy of 96.4%, showcasing the growing potential of mobile AI tools in facilitating early skin cancer diagnosis in clinical and remote settings.

Similarly, AI has been instrumental in advancing lung cancer detection. Borrelli et al., (2021) developed a CNN-based detection system capable of identifying lung lesions in [18F] FDG PET-CT scans with an impressive 90% sensitivity. Expanding on this progress, a 2024 study by Noaman et al., (2024) combined DenseNet201 for deep feature extraction with color histogram features and ML algorithms to further refine early lung cancer detection. Their model, tested on the LC25000 dataset, achieved an outstanding accuracy of 99.68%, surpassing previous state-of-the-art methods and reinforcing AI's potential in thoracic oncology.

AI-driven models are also enhancing early breast cancer prediction. Gjesvik et al., (2024) developed an AI algorithm capable of detecting breast cancer from mammograms taken 4–6 years before clinical diagnosis. In a cohort study involving 116,495 women (aged 50–69 years) across three screening rounds, the model's predictive accuracy improved over time, with ROC curve areas of 0.63, 0.72, and 0.96 for screening-detected cancers, and 0.64, 0.65, and 0.77 for interval cancers. These findings highlight AI's ability to provide long-term predictive insights, enabling earlier intervention and potentially saving lives.

AI is also transforming abdominal cancer diagnostics. Geng et al., (2023) introduced a YOLOv3-based AI model for analyzing abdominal MRI scans, achieving highly accurate 3D axial prescriptions with minimal shifts, mirroring the reproducibility of radiologists inter reader assessments. Meanwhile, (Wu et al., 2023) developed MULLET, a CNN-based AI system for liver lesion segmentation from multi-phase CT images. Their model showed remarkable F2 scores, recall, and precision in distinguishing between malignant tumors and benign lesions, further underscoring AI's role in streamlining liver cancer diagnostics.

In addition to imaging-based cancer detection, AI is enhancing histopathological analysis and disease monitoring. Paige Prostate, an FDA-approved clinical-grade AI tool, assists pathologists in detecting, grading, and quantifying prostate cancer. Using a weakly supervised CNN approach, Paige Prostate achieves an impressive sensitivity of 97.7% and specificity of 99.3%, making it a powerful asset in improving diagnostic consistency and accuracy (Eloy et al., 2023).

Furthermore, AI models have shown diagnostic precision in hematological malignancies, such as CLL, by analyzing blood film morphology. Wang et al., (2023) introduced an automated AI algorithm designed to analyze blood films for detecting lymphocyte features in chronic lymphocytic

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leukemia (CLL). This approach offers comprehensive insights on the course of disease, allowing clinicians to monitor developmental stages more accurately and tailor treatment plans accordingly.

These advancements highlight the remarkable potential of AI in revolutionizing cancer detection. By integrating DL, imaging analysis, and clinical data, AI enhances early cancer detection while boosting the accuracy and efficiency of diagnoses across various cancer types.

3. Patent Status of AI-Mediated Medical Diagnosis

AI has emerged as a transformative force in medical diagnostics, significantly improving disease detection, imaging analysis, and clinical decision-making. As these innovations continue to evolve, securing intellectual property (IP) through patents has become a key focus for researchers, companies, and policymakers.

The patent landscape for AI in medical diagnostics is rapidly expanding, reflecting the increasing recognition of AI's role in healthcare. AI-driven diagnostic tools have received numerous patents (Table 5), including those for imaging-based disease detection, AI-powered pathology analysis, and predictive models for patient outcomes. However, challenges remain in patent eligibility, particularly regarding software-based innovations and the complexities of AI-generated inventions. Additionally, variations in patent regulations across different jurisdictions impact the protection and commercialization of these technologies.

Table 5. Patent status of AI-powered medical diagnosis.

Patent number (year of publication; current status)	Invention	Disease predicted	Reference
IN202141005228 (2021; under examination)	An AI-powered IoT-based automated monitoring system which integrates IoT sensors like temperature and pulse oximeter for detecting, analyzing, and alerting clinicians and authorities about potential COVID-19 infections in individuals.	COVID-19	Gomathi et al., 2021
IN202321075120 (2024; under examination)	An explainable AI-powered system like ML, DL and XAI for detecting, analyzing, and recommending health insights based on infectious disease symptoms, effectively differentiate between bacterial, viral and parasitic infections	Infectious diseases	Kumar et al., 2024
RU0002788393 (2023; granted 2023)	A simple, cost-effective method for differentiating vascular and inflammatory optic nerve disk lesions using ophthalmoscopy and blood test indices (IAL and MVI) for early and accurate diagnosis.	Vascular or inflammatory lesion of the optic disc	Nikolaevna et al., 2023
IN202311047908 (2023; under examination)	This invention presents a hybrid CNN-TLSTM with ATLBO algorithm for real-time dengue disease prediction using Machine Learning and IoT. The system integrates IoT healthcare sensors to collect real-time patient and environmental data, which is processed using Cloud and	Dengue	Gangodkar et al., 2023

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	Fog computing for efficient disease detection.		
IN202341050305 (2023; under examination)	An AI-powered system using deep learning and CNNs to detect and classify pneumonia and COVID-19 from chest X-ray images with high accuracy.	Pneumonia & COVID-19	Suman et al., 2023
IN202111004370 (2021; under examination)	A handheld AI-powered device for detecting, diagnosing, and treating eye infections using a microscopic camera, biosensors, therapeutic sprayers, and a heating cushion.	Eye infections	Giri et al., 2021
IN202211075384 (2022; under examination)	A machine learning-based predictive model combining EGB-multilayer perceptron and RF achieves 97.4% accuracy in early risk assessment of dental caries in children, enhancing dental health outcomes.	Dental caries	Goyal et al., 2022
CN113555087 (2021; under examination)	The invention presents an AI-based film reading method using CNN to improve the accuracy of thyroid cancer diagnosis from ultrasound images. It employs the NanoDet model, integrating ShuffleNetV2 for feature extraction, PAN for feature fusion, and an optimized FCOS detection head to enhance detection efficiency while reducing computational complexity.	Thyroid carcinoma	Shuai et al., 2021
CN112270987 (2021; under examination)	An AI-powered CT-based ovarian cancer diagnosis system leverages adversarial generative networks for automated pathological classification and clinical validation, integrating historical and pathological data to enhance diagnostic accuracy, assist doctors, reduce misdiagnosis, optimize medical resources, improve treatment efficiency, and enable non-invasive classification.	Ovarian cancer	Lei et al., 2021
CN118016279 (2024; under examination)	An AI-driven multimodal platform integrates clinical, genomic, and molecular data to enhance breast cancer diagnosis, prediction, and treatment recommendations. Using machine learning models like SVM, LSTM, and Random Forest, it classifies cancer stages, predicts disease progression, and provides personalized treatment plans with explainable AI insights for clinicians.	Breast cancer	Jiatong et al., 2024
WO2020106185 (2020; under examination)	This invention presents an AI-driven method for detecting and diagnosing	Lung cancer	Vladimirovich et al., 2020

	lung cancer using CT scan images. It analyzes tumor structures through segmentation and chord-based histograms, extracting key features for classification. A Deep Forest machine learning model then distinguishes between malignant and benign tumors, enhancing diagnostic accuracy	

4. Current AI Based Diagnostics Undergoing Clinical Studies

AI-based diagnostics are currently being tested in clinical studies to improve how we detect and treat medical conditions. Currently, numerous AI-based diagnostic tools are undergoing clinical studies (Table 6), aiming to refine and validate their effectiveness in real-world healthcare settings. In order to detect illnesses early and make more accurate diagnoses, these studies concentrate on using machine learning algorithms to analyse medical data, including pictures, genetic information, and patient histories in fields like oncology, cardiology, and neurology. As these AI technologies continue to develop, they have the potential to improve early detection, lead to better patient outcomes, and make healthcare more streamlined and accessible.

Thermalytix is an AI-powered CAD tool designed for early and accurate breast cancer screening. It utilizes high-resolution thermal imaging along with cloud-based analytics to examine thermal patterns in breast tissue. This technology is especially effective for younger women and those with dense breast tissue, where conventional mammograms may have limitations Singh et al., (2021). It can effectively identify breast cancer with 80.5% specificity

Table 6. AI based diagnostic tools undergoing clinical trials (clinicaltrials.gov).

Clinical Reg. No. & Phase	Tool used	Disease	Algorithm	Outcome	Reference
NCT02801877 Completed	Behavioral Intervention Technology	Major Depressive Disorder	ML	Participants showed reduction in Generalized Anxiety Disorder-7	Mohr et al., 2019
NCT04693078 Completed	DEtection of Elusive Polyps (DEEP)	Elusive colonic polyp detection	DL	Able to detect polyps not seen by live real-time endoscopists with 97.1% sensitivity	Livovsky et al., 2021
NCT05593913 Completed	VeriSee AMD	Age related Macular degradation	CNN	Can screen the fundus images with AMD with 96.5% specificity	Hsu et al., 2024
NCT04160988 Completed	VeriSee DR	Diabetic Retinopathy	CNN	Automated image analysis for screening the diabetes retinopathy with 89.9% specificity	Acer Being Health Inc. 2019

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NCT05178095 Completed	Colonoscopy with AI	Gastrointestinal neoplasm & Colonic polyp detection	CNN	NA	Papachrysos, 2025
NCT06036394 Active	AI models	CNS tumors	ML, DL & NLP	NA	Dasgupta, 2023
NCT06335654 Active	CNN	Colorectal neoplasm	SVM	NA	Liu, 2024
NCT06474338 Active	CNN	Bladder tumor	HR-Net	NA	Ye, 2024
NCT05787405 Active	CNN	SARS-CoV-2	Random forest, SVM	NA	Murri, 2023
NCT06332703 Active	CNN	Acanthamoeba keratitis	ResNet101V2	NA	2024
NCT05762991 Active	CNN	Premalignant gastric lesions	QUQDAS-2	NA	Chiang, 2024

5. Limitations

Studies on AI in diagnostic microbiology frequently encounter limitations, including the lack of external datasets for validating algorithms in clinical settings. The scarcity of publicly available datasets for developing DL systems presents significant challenges in result validation (Baowaly et al., 2019). AI systems also struggle with interpreting single-organism polymorphisms and accurately identifying contamination, tasks that require extensive clinical expertise and contextual understanding. Additionally, interpreting antimicrobial susceptibility testing data is complicated by diverse mechanisms of action and overlapping resistances (Shelke et al., 2023).

In oncology, similar challenges arise due to the complexity of cancer types and tumor heterogeneity. Variability in tumor profiles across patients can limit the generalizability of AI algorithms, especially those trained predominantly on specific cancer types or either early- or late-stage disease presentations. Algorithms based on non-representative datasets risk perpetuating healthcare disparities, potentially leading to suboptimal patient outcomes (Feng et al., 2022).

Bias is another critical concern in the development of AI diagnostic tools. It can stem from multiple sources, such as the selection of training data, societal biases embedded within datasets, or cognitive biases of clinicians who label the training data. For example, AI systems for cancer diagnostics may reflect biases in medical imaging datasets. Algorithms trained primarily on images of lighter-skinned individuals may underperform when diagnosing conditions in patients with darker skin tones, exacerbating existing inequities in healthcare (Olsen et al., 2020).

The "black-box" nature of many AI algorithms poses an additional limitation: interpretability. Clinicians need to understand how AI systems make decisions to effectively trust and utilize the technology (Schwartz et al., 2024). A lack of transparency in model outcomes can hinder collaborative decision-making between clinicians and patients, affecting trust and adherence to treatment plans. Without clear explanations for diagnostic outputs, the clinician-patient relationship—an essential aspect of effective healthcare delivery—may be undermined (Challen et al., 2019).

AI tools face practical challenges within clinical settings that limit their impact. The successful implementation of AI diagnostic systems requires synchronization with existing workflows, which can be cumbersome and resource-intensive. Many healthcare facilities lack the infrastructure necessary for seamless integration, resulting in resistance to adopting AI technologies (Papadimitroulas et al., 2021). Moreover, healthcare professionals must possess a certain level of technological literacy to effectively use AI tools (Shafi et al., 2023). By addressing the limitations of AI in medical diagnosis, we can harness its full potential to improve patient outcomes and ensure equitable access to quality care in the evolving landscape of diagnostics.

6. Conclusion

AI is redefining diagnostic practices by integrating predictive modeling, multi-modal imaging, and real-time analysis, making it faster, more accurate, and more efficient—especially in detecting bacterial infections and cancer. With the help of ML and DL, AI-powered tools can identify harmful microbes, predict antibiotic resistance, and detect cancer in medical images with impressive precision. These advancements are reshaping the fields of microbiology and oncology, giving doctors powerful new tools to improve patient care.

Despite these breakthroughs, several challenges remain. The limitations of AI diagnostics include biases in training datasets, lack of external validation, interpretability issues, and integration challenges within clinical workflows. Addressing these challenges requires multidisciplinary collaboration between AI developers, medical professionals, and regulatory bodies to ensure that AI-driven diagnostics are both accurate and ethically sound.

7. Future Aspects

Though AI has revolutionized the field of diagnostics and medical sciences, but the prediction models developed by researchers still lack accuracy and prospective validation. Different prediction model based on imaging analysis of polyps, tumor cells, lesions still lack high resolution capacity in which hidden lesion and different morphologic subtypes could not be identified accurately. Thus, there is still scope of developing a high-resolution AI imaging model which could efficiently identify even the small segments of the lesions. Besides, this there is need to develop AI imaging tools which provides real-time analysis of lesion, tumor segments and polyps which could further assist in quick diagnosis, direct tissue sampling for histopathology analysis, improves accuracy for procedures like tumor resections, improves disease prognosis and could also assist in immediate therapeutic intervention. Besides, the current prediction model based on bacterial infection diagnosis are unable to differentiate between pathogenic and non-pathogenic strain associated with the lesion which could provide false diagnosis. Thus, there is still scope to design better prediction models which could accurately classify the bacterial strain associated with the lesions or tissues.

Abbreviations

AI, Artificial intelligence; AMR, Antimicrobial resistance; ANN, Artificial neural network; BBN, Bayesian Belief Network; CDSS, Clinical decision support system; CFU, Colony forming unit; CLL, Chronic Lymphocytic Leukemia; CNN, Convolutional neuronal network; DL, Deep learning; DNN, Deep neural network; k-NN, k-Nearest Neighbor; MALDI TOF, Matrix assisted laser desorption ionization- Time of flight; ML, Machine learning; MLP, Multilayer perceptron; ; mp-MRI, Multiparametric magnetic resonance imaging; MRSA, Methicillin Resistance *Staphylococcus aureus;* RF, Random Forest; RL, Reinforced learning; RNN, Recurrent Neural Network; ROI, Region of interest; SVM, Support vector machine; WHO, World Health Organization.

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