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Revolutionizing Diagnostics with Artificial Intelligence: Current Innovations, Challenges, and Future Horizons

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REVIEW ARTICLE

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ABSTRACT

Artificial Intelligence (AI) is rapidly transforming the landscape of medical diagnostics, offering unprecedented accuracy, speed, and efficiency in disease detection and decision-making. From image-based analysis in radiology and pathology to predictive analytics in genomics and personalized medicine, AI technologies, particularly machine learning and deep learning, are being increasingly integrated into clinical workflows. These innovations have shown promise in enhancing diagnostic precision, reducing human error, and improving patient outcomes across a wide spectrum of diseases, including cancer, cardiovascular conditions, and infectious diseases. Despite these advancements, the integration of AI into healthcare faces several challenges. Concerns around data privacy, model transparency, algorithmic bias, and clinical validation must be addressed to ensure ethical and reliable deployment. Furthermore, the lack of standardized protocols, regulatory frameworks, and interdisciplinary collaboration hinders the seamless adoption of AI in routine diagnostics. This paper explores the current state of AI in diagnostics, highlights ground-breaking applications already in use, and discusses key limitations that need to be overcome. It also offers insight into future prospects, including explainable AI, integration with wearable technologies, and the potential for AI to support real-time decision-making in point-of-care settings. With continued innovation and responsible implementation, AI holds the potential to revolutionize diagnostic medicine and redefine the future of healthcare.

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Introduction

Definition and scope of Artificial Intelligence (AI) in healthcare

Healthcare costs are expected to fall as a result of AI. Clinical decision-support systems, handy tools that help doctors figure out diagnoses and choose treatments, are probably the most visible form of artificial intelligence you will find in daily hospital work. AI-based CDSSs employ AI models trained on data from patients that are compatible with the use-case at hand, whereas conventional CDSS match the characteristics of individual patients to an existing knowledge base [1]. According to research, AI algorithms have the ability to outperform humans at certain analytical tasks (like imaging pattern recognition, for instance [2].

Significance of AI in laboratory diagnostics

Healthcare AI technology includes both machine learning (ML) and non-ML approaches. Algorithms are used in machine learning, a subset of AI, to analyze datasets for tasks like detection and classification. This makes it possible to autonomously recognize patterns in a variety of domains [3]. Non-ML techniques, on the other hand, concentrate on analysis and prediction without the use of adaptive algorithms and rely on deterministic models and conventional statistical techniques. AI is also being utilized more and more in laboratory medicine for tasks like white blood cell differentials and analyzing antinuclear antibody (ANA) patterns [4].

Objectives of the review

This review article aims to provide a comprehensive analysis of the role of AI in transforming diagnostics, highlighting its current applications, associated challenges, and future prospects. It explores how AI-driven technologies, including machine learning, deep learning, and natural language processing, are enhancing diagnostic accuracy, efficiency, and decision-making across various medical disciplines. Additionally, the review examines the integration of AI in imaging, pathology, genomics, and point-of-care testing, emphasizing its impact on early disease detection and personalized medicine. Key challenges such as data privacy, ethical considerations, algorithmic bias, and the need for regulatory frameworks are critically discussed. Finally, this article outlines emerging trends and future directions, including the role of AI in precision diagnostics, automation, and its potential to bridge global healthcare disparities. Through this review, we aim to provide insights into the evolving landscape of AI in diagnostics, offering perspectives for researchers, clinicians, and policymakers on its responsible and effective implementation in healthcare.

Applications of AI in Medical Laboratory Technology

AI in Diagnostics

Computer vision and time series analysis are some of the major types into which AI interpretation tasks can be divided [5]. In order to generate numerical or symbolic representations of concepts encoded in the image, computer vision algorithms synthesize (or "convolute") high-dimensional image data. It is believed that this procedure imitates how people recognize patterns and derive significant characteristics from pictures. In clinical diagnostics, early computer-vision tools aimed at medical scans-positron emission tomography images, magnetic resonance images-and pathology slides such as histopathological samples quickly became the first AI-fueled products the US Food and Drug Administration (FDA) approved. These first imaging apps include automatic cardiac MRI blood-flow measurement, straightforward echocardiogram ejection-fraction calculations, radiograph-based lung-nodule spotting and volume estimates, mammograms that flag and grade breast density, CT scans that spot strokes, bleeds, and other brain issues, plus turn-key checks for diabetic retinopathy from a routine dilated exam [6][7][8].

The processing of temporal data to predict future observations, identify anomalies within a sequence of observations, or predict the discrete state generating a sequence of observations (e.g., normal heart beat versus arrhythmia) is known as time series analysis. Time series AI algorithms can be used in clinical diagnostics on medical equipment that generate continuous output signals; electrocardiograms are one particularly popular area of study. AI used on ECGs can identify and categorize cardiac contractile failure, blood chemistries associated with aberrant cardiac rhythms, and arrhythmias, particularly atrial fibrillation [9][10][11]. When researchers feed raw DNA sequences into these AI time-series tools, the programs often spotlight tiny but indicative features that hint at where splicing happens, mark vast control regions, and even point toward the products each gene ultimately codes [12].

Automated image analysis

Digital pathology, also known as automated image analysis, is the process of capturing, storing, and interpreting pathologic specimens utilizing digital file formats [13][14]. In early iterations of digital pathology, static images taken by cameras mounted on microscopes were transmitted between distant locations. Later, robotic telepathology evolved from digital pathology, where a pathologist at a distance operated a robotic stage and observed specimens in real time. Full-slide imaging is a more recent development in digital pathology that uses digital slide scanners to produce digital images of full histologic sections. After digitization, the image can be seen using a computer interface that resembles a light microscope's instruments [15].

AI algorithms for infectious disease detection

Smith began with a CNN (Convolutional Neural Network) named Inception 3.0, which had been trained by Google to identify common objects and had only been retrained in the last layers to identify a number of common Gram stain morphologies in positive blood culture smears, including Gram-negative rods, Gram-positive cocci in clusters, and Gram-positive cocci in chains [16]. CNN was trained using a total of 100,000 classified picture crops producing a composite whole slide classification accuracy of 92.5% and a crop classification accuracy of about 95% across all Gram stain categories. The ultimate objective, though, is to execute interpretation with >99% accuracy, which is equivalent to that of a proficient microbiologist [17]. CNNs' ability to improve accuracy as training sets grow in size, which can include millions of photos, is one of their key characteristics.

AI has a lot of potential for use in parasite diagnostics in addition to bacterial smear observation; malaria has received nearly all of the published work to date. Looking at stained thick and thin blood slides under the microscope remains the best way to spot malaria parasites and tell which species is present. Several studies have looked into different AI models to automate image interpretation because there aren't many skilled people in malaria-endemic areas. Frequently, when data is gathered and analyzed in a research setting, these models attain sensitivity and specificities of >95% per image [18][19].

Specimen tracking and laboratory automation systems

Any errors that occur before a specimen is tested, whether during collection, labeling, transportation to a laboratory, laboratory processing, or storage, are referred to as preanalytical errors [20]. Preanalytical error rates range significantly between regions and facilities, primarily due to variations in standards, resources, and control of processes. Barcode-based labeling systems have been used to guarantee that employees follow protocols and increase accuracy in a range of operations [21]. It has been demonstrated that the development and implementation of barcode systems that are intended to complement a particular workflow significantly lowers laboratory specimen misidentifications while also boosting protocol adherence and diagnostic effectiveness in both community-based research in developing nations and hospital-based laboratory settings [22][23].

AI for error reduction and quality control

Recent developments have made it easier to make use of datasets from many sources to train machine learning models collaboratively without exchanging data, which might save researchers a great deal of time and effort compared to manually harmonizing data. In a 2017 blog post, Google introduced Federated Learning, a method that enables a centralized machine learning model to be concurrently trained across multiple dispersed clients without requiring data exchange. One great advantage is that you don't have to worry about manually merging and harmonizing healthcare data from various independent institutions into a single standardized dataset. This is because data sharing is avoided, and each healthcare institution (or client) can simply use its own isolated dataset to train the joint model [24].

Fuzzy Logic has recently been successfully used to train a clinical decision support algorithm for COVID-19 prediction utilizing electronic health records and chest X-rays from numerous healthcare facilities. Using information gathered from 20 different healthcare facilities, a multi-modal neural network model from Florida, called Electronic medical record chest X-ray Artificial Intelligence Model (EXAM), was developed to predict the future oxygen requirements and the 24- or 72-hour prognosis for COVID-19 patients. Remarkably, this was achieved without needing to harmonize or share data. Each "round" of model training involved training the models locally for one epoch using the servers and private data of each institution, and then transmitting the modified model parameters for each local model back to a central server for aggregation. EXAM was able to generalize and attain an average improvement in AUC of 16% over the models trained separately at each location thanks to the FL method, which made it possible to handle vast amounts of data [25][26].

Predictive Analytics

Predictive algorithms, often referred to as clinical prediction models, play a crucial role in diagnosis and prognosis by helping to identify individuals who are more likely to have a particular disease [27]. In today's world of personalized medicine, predictive algorithms are used to guide patients and inform clinical care decisions by focusing on the unique characteristics of each individual, rather than relying on general population averages [28].

AI in Biomarker discovery

In particular, machine learning (ML) and AI techniques have proven effective in analyzing various data modalities for dementia-related disorders and in investigating various biomarkers. These methods are essential for thoroughly analyzing intricate and multimodal data sets in order to find emerging patterns and possible biomarkers [29]. The type of biomarker determines how AI techniques are applied, and these techniques are typically categorized by algorithm learning style and input data. When it comes to biomarker discovery data, supervised learning typically employs input data that has a known classification, such as illness status or an associated endophenotype. Regression, Support Vector Machines (SVMs), random forests, and sophisticated deep learning techniques are all examples of supervised learning. To investigate data and comprehend structure, unsupervised learning techniques are frequently employed. These techniques include dimensional reduction techniques or clustering algorithms to stratify a data set based on feature similarity or to lower the complexity of the data set [30]. A receiver-operating characteristic (ROC) curve is frequently used in targeted fluid-based biomarker development to evaluate the performance and accuracy of new biomarkers during validation phases.

Machine learning models for risk prediction and prognosis.

The accuracy of cancer prediction outcome has greatly increased by 15%-20% in recent years, with the deployment of ML approaches. Machine Learning is a fascinating branch of Artificial Intelligence that tackles the challenge of learning from data samples and ties it all back to the broader idea of making inferences [31]. Every learning algorithm can be broken down into two key stages: first, figuring out the unknown relationships within a system based on the data we have, and second, using those insights to predict how the system will behave in the future [32].

AI in Personalized Medicine

Traditional AI methods typically involve training an algorithm using population data to identify statistical patterns. These patterns can then be applied to diagnose and treat individuals based on their unique demographics and medical history [32]. CURATE.AI is a cutting-edge platform that harnesses the power of AI to map how different levels of treatment (inputs) relate to specific health outcomes (outputs) for each individual, all based on their unique data. To create a personalized CURATE.AI profile for a patient, we analyze how varying doses of medication correlate with measurable results. As the patient's condition changes over time, whether through disease progression or regression, new medications, dose adjustments, or other medical interventions, the CURATE. AI profile adapts accordingly, ensuring that the care provided is always tailored to their evolving needs throughout the entire treatment journey. The CURATE. AI technique has been proven effective for optimizing single-drug therapies, combination treatments, cancer care, and immunosuppressive therapies, as well as for both retrospective and prospective dosage adjustments. A recent study has revealed that this approach can also be utilized for cognitive training, paving the way for new applications [33][34].

Integrating AI with literary scientific data

AI greatly reduces the time spent on literature searches, study evaluation, data extraction, and evidence aggregation. This efficiency enables researchers and doctors to concentrate more on analysis and interpretation, expediting the speed of scientific discovery and therapeutic decision-making [35]. AI generates consistent judgments and appraisals while minimizing error by humans and subjective bias. Consistency is especially critical in systematic reviews and guideline formulation, because discrepancies in evaluation might result in incompatible conclusions and recommendations [36]. AI can process vast amounts of data, making it possible to keep up with the rising quantity of scientific research. This scalability is essential for thorough systematic reviews and for keeping clinical guidelines up to date [37].

Key Technologies Driving AI in Laboratories

Machine learning and deep learning algorithms

Machine learning is being harnessed to predict test results based on other available data, helping to cut down on unnecessary testing. By analyzing retrospective, integrated data sets that include relevant lab values, patient demographics, and clinical labels from diagnosis codes or provider notes, researchers are exploring the clinical significance of different components in multianalyte panel tests. This is especially true for tests related to specific organ systems, like the liver panel, or physiological processes, such as the iron deficiency panel [38][39]. When it comes to multianalyte tests, other researchers have also explored ways to gauge the diagnostic value of a test by looking at the results of related tests. For instance, Zhang and colleagues found that a patient's history of cancer, along with Complete Blood Count (CBC) and differential test results, can help predict whether the findings from peripheral blood flow cytometry will be abnormal. This approach could potentially cut down unnecessary use of peripheral blood flow cytometry by 35-50% [40][41].

Image recognition and computer vision for diagnostic imaging.

These tools allow us to capture, interpret, analyze, and understand countless static and dynamic images in real time. This leads to a more accurate characterization of various diseases and helps in selecting patients for early treatments. Many of the diagnostic methods we have today can be invasive, costly, or overly complex to standardize in many parts of the world. That's where AI comes in as a practical solution, enabling us to identify a wide range of diseases at their early stages. This not only helps in defining better treatment plans and follow-ups but also reduces the medical costs associated with each patient. The combination of high-performance computing with machine learning (ML) enables the processing of large amounts of medical imagine data in order to provide accurate and efficient evaluations.

CV (Computer Vision) works with a wide range of challenges, including picture categorization, identification of objects, detection, and reconstruction. It seeks to model and understand the visual environment by extracting usable information from digital images, which is typically motivated by challenging human vision tasks. Although it has existed since the 1960s, it remains an unresolved and difficult job, with computers just recently providing viable solutions in a variety of application domains. It is a multidisciplinary field that is closely related to artificial intelligence. AI is a vast field of computer science that seeks to develop automatic ways for solving issues that traditionally need human intelligence. ML, in turn, is a subset of AI that creates systems capable of automatically learning from data and experiences. The most successful CV systems were built using machine learning techniques [41][42].

Deep learning (DL) is a fascinating branch of machine learning that has gained a lot of traction in computer vision (CV) because of its impressive ability to tackle complex tasks related to analyzing and interpreting visual data. The "deep" in deep learning refers to neural networks that consist of multiple layers. In recent years, there has been an increasing interest in applying deep learning models to medical issues. Deep neural networks, for example, have demonstrated remarkable performance in skin lesion classification tests. CNNs frequently outperform due to their enhanced segmentation performance, despite their reliance on vast amounts of training data [43].

Robotics in automated laboratory processes

In manufacturing, automation is described as the technology that allows an operation to be completed without the need for human intervention. Humans may be present as observers or participants, but the procedure is self-driven. As a result, the degree of automation of a system is defined as the ratio of already automated processes to the overall number of all operations of the system. Automation speeds up the process of translating research findings into therapeutic applications [44].

Benefits of AI in Laboratory Medicine

Enhanced accuracy and efficiency in diagnostic processes

AI is fundamentally changing the field of diagnostic imaging in healthcare. This technique, which combines complex algorithms and machine learning, offers a significant step forward in the interpretation and application of medical imaging such as X-rays, MRIs, and CT scans. AI's function in diagnostic imaging is more than just automating operations; it fundamentally alters the approach to disease detection, making it more accurate and efficient [45]. Furthermore, artificial intelligence improves diagnostic accuracy. AI systems can spot patterns and irregularities in medical images that the human eye may miss. AI's efficacy in Enhanced Image Analysis is especially notable. It excels at detecting complicated patterns in medical images, identifying irregularities that are typically unnoticeable to the human eye, hence considerably increasing the accuracy of diagnoses in complex cases like cancer or neurological disorders [46][47][47][48[49].

Reduction in human error and turnaround time

Traditional methods of interpreting images can take a lot of time and are often susceptible to human mistakes. However, AI can interpret and analyze images considerably faster, drastically lowering the time it takes to diagnose a patient. This quickness is especially important in emergency situations, where every second counts [46]. AI plays an important role in reducing human error. AI makes significant contributions in terms of efficiency and speed, substantially accelerating the process of evaluating medical images. This acceleration is crucial, not just for convenience, but for potentially life-saving situations where quick treatment decisions are required [50][51][52].

Cost-effectiveness in high-volume testing environments

AI plays a huge role in making healthcare more cost-effective. By boosting efficiency and accuracy, it cuts down on the need for repetitive scans and lowers the chances of misdiagnosis, ultimately helping to bring down overall healthcare costs. For instance, AI-powered convolutional neural networks (CNNs) not only matched the sensitivity of expert radiologists but also identified 8.4% of lung nodules that might have been missed in patients with complicated lung conditions. This advancement significantly boosts the speed and efficiency of diagnostic processes [50]. A recent study on the cost-effectiveness of caries detection highlighted how AI can swiftly process and analyze large volumes of data using advanced detection methods. This really showcased the significant time-saving advantages that AI brings to dental imaging analysis. The AI system notably cut down the time required for image interpretation, emphasizing the efficiency improvements in dental diagnostics [53][55].

Improved patient outcomes through precision diagnostics

One of the key advantages of AI is its ability to forecast. By shifting through previous data, AI can identify trends and potential risk factors, which allows for the early detection of diseases. The majority of health care providers believe that the introduction and substantial use of EHR will reduce operating costs, reduce error rates, and improve patient outcomes. EHRs: 1) increased the comprehensiveness of patient contacts, 2) supported patient queries, 3) minimized ambiguity due to illegible handwriting, and 4) strengthened doctors' confidence in the EHR system [56].

Challenges and Limitations

Data quality and availability (bias, inconsistency)

Clinical research might rely on a single method at a central lab, but the findings from these studies won't be truly useful unless all other methods align with that central lab approach. When we mix compromised medical advice into AI models that deal with patients who have test results that just don't match up, it can lead to incorrect or unsuitable treatments [57][58].

Integration challenges with existing laboratory systems

The performance of ML models offers a key difficulty in the field of AI. The quality of the data used has a significant impact on algorithm performance. The source of the training data plays a key influence in molding the future or intended use. When modeling with large datasets, concerns like inappropriate fitting and restricted data volume typically result in poor model performance [58]. Furthermore, ensuring uniformity in algorithm performance while using AI systems demands attentive mitigation of component failure.

Different clinical centers frequently use different data collection and testing systems. The lack of open data access and data sharing platforms causes the formation of separate data repositories. As a result, prior to adopting AI-based analysis, it is critical to create specialized server software and standardize data interfaces. Mohn *et al*. study exemplifies this technique, as they improved the versatility of current models across varied institutions by optimizing them with locally acquired data [59].

Ethical and regulatory concerns (data privacy, AI accountability)

Ethical problems, such as accountability, privacy, and transparency, impede the mainstream implementation of artificial intelligence. It is critical to strengthen the framework for responsibility management and clearly define the roles and responsibilities of medical institutions, programmers, and medical specialists throughout the AI deployment process. Protecting patients' privacy can occasionally undermine the transparency and comprehensibility of artificial intelligence systems [60][61]. This occurs when data stays unavailable to the public or the complexities of ML model design are unknown. To address this limitation, a multi-center RF prognosis prediction model was developed to improve prognostic forecasts while protecting privacy. For example, AI bias is a technical challenge that can unintentionally lead to bias towards specific populations. Healthcare providers should focus more on lobbying for this technology while also addressing patients' emotional well-being.

Resistance to adoption due to lack of technical expertise

While great progress has been achieved in the application of AI in medical laboratory exams, the requirement for computer science knowledge and the analysis of massive clinical data have limited its broader implementation [62]. A web-based poll on the use of AI, which included participants such as doctors (26%) and laboratory managers (22%), found a lack of specific AI understanding in the healthcare sector. This emphasizes the critical need for AI education to enable the application of AI into diagnostic methods. Regarding human-machine interaction, the significance for AI's advancement toward higher intelligence becomes clear [63].

Case Studies and Real-World Examples

Applications of AI in automated blood tests and hematology analyzers

Childhood Acute Lymphoblastic Leukemia (ALL) is a serious type of cancer and the leading cause of cancer-related deaths in children. Unfortunately, about 20% of children who receive treatment for it end up relapsing. It's really important to anticipate relapses so we can effectively address the various risk groups. This helps us manage and plan follow-ups more efficiently. Pan *et al.* [64] developed a model to predict relapses in Acute Lymphoblastic Leukemia (ALL) using machine learning algorithms. This model helps categorize patients into different risk groups. In the process of selecting the best model, he utilized 103 clinical variables to train four different classification algorithms: random forest (RF), decision tree, SVM and linear regression. These algorithms work together to differentiate between relapses and non-relapses across three defined risk categories: standard, intermediate, and high risk. While Pan *et al.* created a model to forecast disease relapse, Hauser *et al.* [65] explored the potential of predicting Chronic Myeloid Leukemia (CML) before diagnosis by relying solely on CBC test results and machine learning algorithms like XGBoost and LASSO, analyzing data from 1,623 patients with confirmed CML status. The study took into account various factors, including laboratory CBC results, patient demographics such as age and gender, and details from patient encounters. To assess the predictive power of the most promising indicators, we employed a prospective feature selection process. The dataset was divided into seven groups, using the time of diagnosis as a baseline for patients, while the other six groups represented different time frames leading up to the diagnostic test. Interestingly, the selection of variables revealed different features to consider in the models, depending on the interval during which the data was collected.

The outcome of the selected categories in conducted using a 10-fold cross-validation method across each of the 100 training sets. However, it's important to note that this proposed approach falls short for internal validation, which actually requires a minimum of 50 repetitions. However, the selected data set in [65] was split into two clear groups: the train/validation group and the test group. While using this split-sample validation method is reasonable and justifiable in this case due to the large sample size, it can lead to some significant issues. There are many factors that need to be considered throughout the program. For example, because the sample split was done completely at random, there could have been significant patient imbalances in terms of predictor distribution and output. Furthermore, 20% was used for model evaluation, resulting in a potentially skewed appraisal of the model's outcomes.

AI in cancer diagnostics through histopathological imaging

Presently, latest advances in AI have opened new horizons for drastically changing the process using which cancer is identified and categorized. Different artificial intelligence systems are exponentially being employed to deliver information that is challenging for pathologists to classify [66][67]. For example, assessing immunohistochemical biomarkers, like Ki67 and PD-L1, accurately and objectively could involve quantifying cells, evaluating how they're arranged spatially, as well as looking at aspects like their expression, density, and distribution patterns. AI can play a crucial role in spotting isolated tumor cells in lymph nodes that raise concerns for metastatic carcinoma, enhancing detection sensitivity and saving valuable time. Additionally, AI technologies can help standardize scoring systems for certain tumors, like the Gleason score for prostate cancers or grading for breast cancer, where the morphological characteristics are represented along a spectrum of a continuous biological process [68]. One interesting use of AI search techniques is in content-based image retrieval (CBIR). This technology enables pathologists to find images that are similar to a specific image from a vast histopathology database. It's particularly beneficial for helping pathologists diagnose rare and complex cases they might face in their clinical work. The images retrieved from the database highlight similarities in related histological features, not just visual resemblance. Consequently, CBIR streamlines the process of delivering accurate diagnoses quickly, even for challenging cases [69].

AI systems used during the COVID-19 pandemic for testing and triage

The CURIAL-1.0 artificial intelligence screening test effectively diagnosed patients who came to the emergency department with COVID-19. It did this by using simple blood tests, blood gas analysis, and vital signs collected within an hour of their arrival at the hospital. CURIAL-Lab is a specialized model that focuses on a unique set of routine blood tests, including FBC, urea, creatinine, electrolytes, LFTs, and CRP. It intentionally leaves out coagulation panels and blood gas tests, as these aren't always performed universally and tend to offer less valuable information [70].

Future Directions and Opportunities

Development of explainable AI models to enhance trust

Explainable AI is the ability of AI systems to provide human-readable explanations for their decisions and suggestions. It lets clinicians and patients to understand the elements that influence an AI model's output, building confidence and allowing informed decision-making. Explain ability is important in healthcare because it enhances patient safety, improves clinical decision-making, allows for successful collaboration between physicians and AI, and ensures ethical and legal compliance [71].

Integration of multi-omics data for comprehensive diagnostics.

Disease identification and diagnosis are accelerated using artificial intelligence technology, imaging, molecular, and cellular data. The relationship of non-coding RNA (ncRNA) with diseases has been established, allowing scientists to investigate disease causes and, ultimately, finding medication for those diseases. Complicated disorders, such as cardiovascular disease, breast cancer, and lung cancer, are linked to aberrant ncRNA expression, especially lncRNAs. The computational methods focus on uncovering possible connections between ncRNA and diseases by leveraging biological data, including genomic locations and tissue specificity. Identifying these relationships helps to better understand the pathogenesis, diagnosis, and therapy of human diseases. Similarly, differential gene expression has been utilized to diagnose diseases [72].

Current methods for prediction of links between ncRNAs and disorders are divided into two categories: network-based and machine-learning-based methods. The network-based approaches make use of diverse networks, such as lncRNA-disease, lncRNA-miRNA, and miRNA-disease datasets with established relationships. Machine-learning methods, on the other hand, forecast probable associations by developing models that are trained using association data to enhance accuracy highlighted the need to combine clinical data, digital pathology, and genomic and transcriptomic profiles to better predict how patients will respond to breast cancer therapies. In a study called the multi-omics graph convolutional network (MOGONET), researchers introduced a supervised classification framework that leverages various types of multi-omics data for biomedical categorization [73]. A new model that integrates multiple omics data using a graph convolutional network (GCN) has been introduced to assess and categorize different cancer subtypes predicted miRNA-disease connections that stem from lncRNA-miRNA interactions and convolutional networks [74]. There are also various machine learning methods like PLRPIM, DRPLPI, GPLPI, and GAE-LGA for predicting interactions among biomolecules, like lncRNA-protein interactions [75]. Some researchers have created innovative multi-omics integration tools like CustOmics. This tool leverages deep learning to bring together complex, high-dimensional, and diverse data sets.

Expansion of AI in point-of-care testing (POCT)

Point-of-Care Testing (POCT) that is simple to use and integrates with medical records or a larger health surveillance system has the potential to significantly reduce disease burdens via home or self-testing. Patients who may delay getting medical care for a stigmatized ailment could do testing without having to report to a public health facility or physician's office. A modern example, using an autonomous machine learning approach, may detect real-world latent viral diseases. This is done by withdrawing substantial data from social media, based on sentiment analysis [76].

Conclusion

Artificial intelligence is reshaping the landscape of medical laboratory diagnostics, offering unprecedented advancements in accuracy, efficiency, and personalized medicine. By automating image analysis, optimizing workflows, and leveraging predictive analytics, AI is enhancing diagnostic capabilities while reducing human error and turnaround time. Technologies such as machine learning, deep learning, and computer vision have revolutionized laboratory medicine, biomarker discovery, and tailored treatment strategies. Despite these promising developments, challenges remain, including issues of data quality, integration hurdles, ethical concerns, and resistance to adoption. Moving forward, the development of explainable AI models, integration of multi-omics data, and expansion into point-of-care testing will further elevate the role of AI in laboratory medicine. The continued evolution of AI-driven diagnostics holds great promise in delivering more precise, accessible, and efficient healthcare solutions.

Authors' contributions

ICMJE criteria	Details	Author(s)
1. Substantial contributions	Conception, OR	1,5
	Design of the work, OR	2,4
	Data acquisition, analysis, or interpretation	3
2. Drafting or reviewing	Draft the work, OR	1,2,5
	Review critically for important intellectual content	3,4
3. Final approval	Approve the version to be published	1,2,3,4,5
4. Accountable	Agree to be accountable for all aspects of the work	1,2,3,4,5

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Declarations

Ethics approval and consent to participate

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Consent for publication

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Competing interests

The authors declare no competing interests.

References

[1]. Higgins D, Madai VI. From bit to bedside: a practical framework for artificial intelligence product development in healthcare. Adv Intell Syst. 2020;2(10):2000052.

[2]. Shortliffe EH, Sepúlveda MJ. Clinical decision support in the era of artificial intelligence. Jama. 2018;320(21):2199-200.

[3]. Loh TP, Cervinski MA, Katayev A, Bietenbeck A, van Rossum H, Badrick T. Recommendations for laboratory informatics specifications needed for the application of patient-based real time quality control. Clin Chim Acta. 2019;495:625-9.

[4]. Intra J, Taverna E, Sala MR, Falbo R, Cappellini F, Brambilla P. Detection of intestinal parasites by use of the cuvette-based automated microscopy analyser sediMAX®. Clin Microbiol Infect. 2016;22(3):279-84.

[5]. Torkamani A, Andersen KG, Steinhubl SR, Topol EJ. High-definition medicine. Cell. 2017;170(5):828-43.

[6]. Retson TA, Besser AH, Sall S, Golden D, Hsiao A. Machine learning and deep neural networks in thoracic and cardiovascular imaging. J Thorac Imaging. 2019;34(3):192-201.

[7]. Asch FM, Abraham T, Jankowski M, Cleve J, Adams M, Romano N, et al. Accuracy and reproducibility of a novel artificial intelligence deep learning-based algorithm for automated calculation of ejection fraction in echocardiography. J Am Coll Cardiol. 2019;73(9S1):1447.

[8]. Le E, Wang Y, Huang Y, Hickman S, Gilbert F. Artificial intelligence in breast imaging. Clin. Radiol. 2019;74(5):357-66.

[9]. Hannun AY, Rajpurkar P, Haghpanahi M, Tison GH, Bourn C, Turakhia MP, et al. Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. Nat Med. 2019;25(1):65-9.

[10]. Attia ZI, Kapa S, Lopez-Jimenez F, McKie PM, Ladewig DJ, Satam G, et al. Screening for cardiac contractile dysfunction using an artificial intelligence–enabled electrocardiogram. Nat Med. 2019;25(1):70-4.

[11]. Galloway CD, Valys AV, Shreibati JB, Treiman DL, Petterson FL, Gundotra VP, et al. Development and validation of a deep-learning model to screen for hyperkalemia from the electrocardiogram. JAMA cardiology. 2019;4(5):428-36.

[12]. Jaganathan K, Panagiotopoulou SK, McRae JF, Darbandi SF, Knowles D, Li YI, et al. Predicting splicing from primary sequence with deep learning. Cell. 2019;176(3):535-48.

[13]. Wang J, Cao H, Zhang JZ, Qi Y. Computational protein design with deep learning neural networks. Sci Rep. 2018;8(1):1-9.

[14]. Erikson GA, Bodian DL, Rueda M, Molparia B, Scott ER, Scott-Van Zeeland AA, et al. Whole-genome

sequencing of a healthy aging cohort. Cell. 2016;165(4):1002-11.
[15]. 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):e01521-17.
[16]. Samuel LP, Balada-Llasat J-M, Harrington A, Cavagnolo R. Multicenter assessment of gram stain error rates. J Clin Microbiol. 2016;54(6):1442-7.
[17]. Barry-Straume J, Tschannen A, Engels DW, Fine E. An evaluation of training size impact on validation accuracy for optimized convolutional neural networks. SMU Data Science Rev. 2018;1(4):12.
[18]. Poostchi M, Ersoy I, McMenamin K, Gordon E, Palaniappan N, Pierce S, et al. Malaria parasite detection and cell counting for human and mouse using thin blood smear microscopy. J. Med. Imaging. 2018;5(4):044506.
[19]. Poostchi M, Silamut K, Maude RJ, Jaeger S, Thoma G. Image analysis and machine learning for detecting malaria. Trans Res. 2018;194:36-55.
[20]. Rajaraman S, Antani SK, Poostchi M, Silamut K, Hossain MA, Maude RJ, et al. Pre-trained convolutional neural networks as feature extractors toward improved malaria parasite detection in thin blood smear images. PeerJ. 2018;6:e4568.
[21]. Rajaraman S, Jaeger S, Antani SK. Performance evaluation of deep neural ensembles toward malaria parasite detection in thin-blood smear images. PeerJ. 2019;7:e6977.
[22]. Plebani M. Quality indicators to detect pre-analytical errors in laboratory testing. The Clin Biochem Rev. 2012;33(3):85-8.
[23]. Zarbo RJ, Tuthill JM, D'Angelo R, Varney R, Mahar B, Neuman C, et al. The Henry Ford Production System: reduction of surgical pathology in-process misidentification defects by bar code-specified work process standardization. J Clin Pathol. 2009;131(4):468-77.
[24]. Connor NE, Manary MJ, Maleta K. Monitoring the adequacy of catch-up growth among moderately malnourished children receiving home-based therapy using mid-upper arm circumference in southern Malawi. Matern Child Health J. 2011;15(7):980-4.
[25]. McMahan B, Ramage D. Federated learning: Collaborative machine learning without centralized training data. Google Research Blog. 2017;3.
[26]. Dayan I, Roth HR, Zhong A, Harouni A, Gentili A, Abidin AZ, et al. Federated learning for predicting clinical outcomes in patients with COVID-19. Nature Med. 2021;27(10):1735-43.
[27]. Christodoulou E, Ma J, Collins GS, Steyerberg EW, Verbakel JY, Van Calster B. A systematic review shows no performance benefit of machine learning over logistic regression for clinical prediction models. J Clin Epidemiol. 2019;110:12-22.
[28]. Shah ND, Steyerberg EW, Kent DM. Big data and predictive analytics: recalibrating expectations. Jama. 2018;320(1):27-8.
[29]. Beam AL, Kohane IS. Big data and machine learning in health care. Jama. 2018;319(13):1317-8.
[30]. Myszczynska MA, Ojamies PN, Lacoste AM, Neil D, Saffari A, Mead R, et al. Applications of machine learning to diagnosis and treatment of neurodegenerative diseases. Nat. Rev. Neurol. 2020;16(8):440-56.
[31]. Niknejad A, Petrovic D. Introduction to computational intelligence techniques and areas of their applications in medicine. Med Appl Artif Intell. 2013;51:201.
[32]. Ngiam KY, Khor W. Big data and machine learning algorithms for health-care delivery. Lancet Oncol. 2019;20(5):e262-73.
[33]. Zarrinpar A, Lee D-K, Silva A, Datta N, Kee T, Eriksen C, et al. Individualizing liver transplant immunosuppression using a phenotypic personalized medicine platform. Sci Transl Med. 2016;8(333):333ra49.
[34]. Lee D-K, Chang VY, Kee T, Ho C-M, Ho D. Optimizing combination therapy for acute lymphoblastic leukemia using a phenotypic personalized medicine digital health platform: Retrospective optimization individualizes patient regimens to maximize efficacy and safety. Slas Technology Sci Innov. 2017;22(3):276-88.
[35]. Pantuck AJ, Lee DK, Kee T, Wang P, Lakhotia S, Silverman MH, et al. Modulating BET bromodomain inhibitor ZEN-3694 and enzalutamide combination dosing in a metastatic prostate cancer patient using CURATE. AI, an artificial intelligence platform. Advanc Ther. 2018;1(6):1800104.
[36]. Kee T, Weiyan C, Blasiak A, Wang P, Chong JK, Chen J, et al. Harnessing CURATE. AI as a digital therapeutics platform by identifying N-of-1 learning trajectory profiles. Advanc Ther. 2019;2(9):1900023.
[37]. Van Altena A, Spijker R, Olabarriaga S. Usage of automation tools in systematic reviews. Res Synth Methods. 2019;10(1):72-82.
[38]. Hair K, Wilson E, Wong C, Tsang A, Macleod M, Bannach-Brown A. Systematic online living evidence summaries: emerging tools to accelerate evidence synthesis. Clin Sci. 2023;137(10):773-84.
[39]. Lidbury BA, Richardson AM, Badrick T. Assessment of machine-learning techniques on large pathology data sets to address assay redundancy in routine liver function test profiles. Diagnosis. 2015;2(1):41-51.
[40]. Zhang ML, Guo AX, Kadauke S, Dighe AS, Baron JM, Sohani AR. Machine learning models improve the diagnostic yield of peripheral blood flow cytometry. AJP. 2020;153(2):235-42.
[41]. Richardson AM, Lidbury BA. Infection status outcome, machine learning method and virus type interact to affect the optimised prediction of hepatitis virus immunoassay results from routine pathology laboratory assays in unbalanced data. BMC Bioinformatics. 2013;14:1-8.

[42]. Shen D, Wu G, Suk H-I. Deep learning in medical image analysis. Annu Rev Biomed Eng. 2017;19(1):221-48.
[43]. Chen C, Qin C, Qiu H, Tarroni G, Duan J, Bai W, et al. Deep learning for cardiac image segmentation: a review. Front Cardiovasc Med. 2020;7:25.
[44]. Holland I, Davies JA. Automation in the life science research laboratory. Front Bioeng Biotechnol. 2020;8:571777.
[45]. Najjar R. Redefining radiology: a review of artificial intelligence integration in medical imaging. Diagnostics. 2023;13(17):2760.
[46]. Srivastav S, Chandrakar R, Gupta S, Babhulkar V, Agrawal S, Jaiswal A, et al. ChatGPT in radiology: the advantages and limitations of artificial intelligence for medical imaging diagnosis. Cureus. 2023;15(7):e41435.
[47]. Ipp E, Liljenquist D, Bode B, Shah VN, Silverstein S, Regillo CD, et al. Pivotal evaluation of an artificial intelligence system for autonomous detection of referrable and vision-threatening diabetic retinopathy. JAMA Netw Open. 2021;4(11):e2134254-e.
[48]. Luo H, Xu G, Li C, He L, Luo L, Wang Z, et al. Real-time artificial intelligence for detection of upper gastrointestinal cancer by endoscopy: a multicentre, case-control, diagnostic study. Lancet Oncol. 2019;20(12):1645-54.
[49]. Waldstein SM, Vogl W-D, Bogunovic H, Sadeghipour A, Riedl S, Schmidt-Erfurth U. Characterization of drusen and hyperreflective foci as biomarkers for disease progression in age-related macular degeneration using artificial intelligence in optical coherence tomography. JAMA Ophthalmol. 2020;138(7):740-7.
[50]. Abadia AF, Yacoub B, Stringer N, Snoddy M, Kocher M, Schoepf UJ, et al. Diagnostic accuracy and performance of artificial intelligence in detecting lung nodules in patients with complex lung disease: a noninferiority study. J Thorac Imaging. 2022;37(3):154-61.
[51]. Yang X, Wang H, Dong Q, Xu Y, Liu H, Ma X, et al. An artificial intelligence system for distinguishing between gastrointestinal stromal tumors and leiomyomas using endoscopic ultrasonography. Endoscopy. 2022;54(03):251-61.
[52]. Zhang Y, Cui J, Wan W, Liu J. Multimodal imaging under artificial intelligence algorithm for the diagnosis of liver cancer and its relationship with expressions of EZH2 and p57. Comput Intell Neuro. 2022;2022(1):4081654.
[53]. Nam JG, Hwang EJ, Kim J, Park N, Lee EH, Kim HJ, et al. AI improves nodule detection on chest radiographs in a health screening population: a randomized controlled trial. Radiology. 2023;307(2):e221894.
[54]. Park A, Chute C, Rajpurkar P, Lou J, Ball RL, Shpanskaya K, et al. Deep learning–assisted diagnosis of cerebral aneurysms using the HeadXNet model. JAMA Netw Open. 2019;2(6):e195600-e.
[55]. Wang D, Xu J, Zhang Z, Li S, Zhang X, Zhou Y, et al. Evaluation of rectal cancer circumferential resection margin using faster region-based convolutional neural network in high-resolution magnetic resonance images. Dis Colon Rectum. 2020;63(2):143-51.
[56]. van Schrojenstein Lantman M, van de Logt A-E, Thelen M, Wetzels JF, van Berkel M. Serum albumin measurement in nephrology: room for improvement. Nephrol Dial Transplant. 2022;37(10):1792-9.
[57]. Tan K, Tang K, Putra A, Pu X, Huang S, Lee T, et al. An auto-perfusing umbilical cord blood collection instrument. ISA Trans. 2012;51(3):420-9.
[58]. Mey F, Clauwaert J, Van Huffel K, Waegeman W, De Mey M. Improving the performance of machine learning models for biotechnology: The quest for deus ex machina. Biotechnol Adv. 2021;53:107858.
[59]. DeYoung B, Morales M, Giglio S. Microbiology 2.0–A "behind the scenes" consideration for artificial intelligence applications for interpretive culture plate reading in routine diagnostic laboratories. Front Microbiol. 2022;13:976068.
[60]. Mohn SF, Law M, Koleva M, Lee B, Berg A, Murray N, et al. Machine learning model for chest radiographs: Using local data to enhance performance. Can Assoc Radiol J. 2023;74(3):548-56.
[61]. Alrefaei AF, Hawsawi YM, Almaleki D, Alafif T, Alzahrani FA, Bakhrebah MA. Genetic data sharing and artificial intelligence in the era of personalized medicine based on a cross-sectional analysis of the Saudi human genome program. Sci Rep. 2022;12(1):1405.
[62]. Koçak B, Cuocolo R, Dos Santos DP, Stanzione A, Ugga L. Must-have qualities of clinical research on artificial intelligence and machine learning. Balkan Med J. 2023;40(1):3.
[63]. Paranjape K, Schinkel M, Hammer RD, Schouten B, Nannan Panday R, Elbers PW, et al. The value of artificial intelligence in laboratory medicine: current opinions and barriers to implementation. AJP. 2021;155(6):823-31.
[64]. Pan L, Liu G, Lin F, Zhong S, Xia H, Sun X, et al. Machine learning applications for prediction of relapse in childhood acute lymphoblastic leukemia. Sci Rep. 2017;7(1):7402.
[65]. Hauser RG, Esserman D, Beste LA, Ong SY, Colomb DG, Jr, Bhargava A, et al. A Machine Learning Model to Successfully Predict Future Diagnosis of Chronic Myelogenous Leukemia With Retrospective Electronic Health Records Data. AJP. 2021;156(6):1142-8.
[66]. Ameen MU, Ashfaq M, Shahbaz F, Dilbar M, Ali A, Jamil I. Transforming Histopathology with Artificial Intelligence: Enhancing Diagnosis, Prognosis, and Personalized Care. MSRA. 2025;3(3):64-76.
[67]. Ibrahim A, Gamble P, Jaroensri R, Abdelsamea MM, Mermel CH, Chen PHC, et al. Artificial intelligence in

digital breast pathology: techniques and applications. The Breast. 2020;49:267-73.
[68]. Rehman H, Hassan M, Umar M, Qurban A, Khawar H. Study to identify the signalling cascade behind expression level of PTEN and RB1 gene in breast cancer. Rep Glob Health Res. 2022;5:142.
[69]. Hegde N, Hipp JD, Liu Y, Emmert-Buck M, Reif E, Smilkov D, et al. Similar image search for histopathology: SMILY. NPJ Digit Med. 2019;2(1):56.
[70]. Soltan AA, Kouchaki S, Zhu T, Kiyasseh D, Taylor T, Hussain ZB, et al. Rapid triage for COVID-19 using routine clinical data for patients attending hospital: development and prospective validation of an artificial intelligence screening test. The Lancet Dig Health. 2021;3(2):e78-87.
[71]. Hicks SA, Strümke I, Thambawita V, Hammou M, Riegler MA, Halvorsen P, et al. On evaluation metrics for medical applications of artificial intelligence. Sci Rep. 2022;12(1):5979.
[72]. Zhang S, Jiang H, Gao B, Yang W, Wang G. Identification of diagnostic markers for breast cancer based on differential gene expression and pathway network. Front Cell Dev Biol. 2022;9:811585.
[73]. Wang T, Shao W, Huang Z, Tang H, Zhang J, Ding Z, et al. MOGONET integrates multi-omics data using graph convolutional networks allowing patient classification and biomarker identification. Nat Commun. 2021;12(1):3445.
[74]. Wang W, Chen H. Predicting miRNA-disease associations based on lncRNA–miRNA interactions and graph convolution networks. Brief Bioinform. 2023;24(1):bbac495.
[75]. Wekesa JS, Meng J, Luan Y. Multi-feature fusion for deep learning to predict plant lncRNA-protein interaction. Genomics. 2020;112(5):2928-36.
[76]. Fatima K, Haroon H, Laraib I, Jabbar E, Yousaf F, Jamil I. Integrating rapid diagnostics, AI technologies, and omics approaches for sepsis management and antimicrobial stewardship. J Med Health Sci Rev. 2025;2(2):6084-6101.