The Future of AI in Laboratory Medicine: Advancing Diagnostics, Personalization, and Healthcare Innovation

Md Habibur Rahman[1], Md Abdur Rahman Biswash[2], Asim Debnath[3], Md Abu Bakar Siddique[4], Md Mostafizur Rahman[4], Md Mehedi Hasan[5], Moushumi Afroza Mou[4]

Abstract
Artificial intelligence (AI) has brought a wave of transformation to laboratory medicine, enhancing the accuracy and efficiency of diagnostics. Traditionally, AI has evolved from abstract theories to complex systems capable of replicating human cognitive functions and performing sophisticated analytical tasks. The current applications, especially in machine learning and deep learning, empower laboratories with the tools to handle large datasets and make predictive analysis a reality, thus revolutionizing the field of diagnostics and personalized medicine. Artificial intelligence can complement clinical chemistry and medical imaging analysis through automated systems, which help diagnostics by detecting complex patterns and generating reliable results. Automating image analysis, predictive analytics, and diagnostic decision support systems will be critical in linking AI with EHRs and next-generation sequencing data. Such developments enable early disease detection, better resource allocation, and personalized health strategies for individual patients. Despite its promise, challenges persist, including those related to regulatory compliance, data consistency, ethical concerns, and transparency. Key to integration into clinical practice is ensuring full validation, addressing the "black box" problem, and mitigating risks associated with AI-driven decisions. Future directions will highlight the importance of AI as a cognitive partner to clinicians, combining large datasets to expand diagnostics and advance personalized medicine. Continued investment in AI research, professional training, and ethical oversight is essential to maximize its potential. AI's transformative impact on laboratory medicine promises to improve outcomes, optimize workflows, and reshape healthcare delivery, offering innovative solutions to longstanding medical challenges.

Keywords: Artificial Intelligence, Laboratory Medicine, Diagnostics, Machine Learning, Personalized Medicine

Significance | Artificial intelligence enhances laboratory medicine by improving diagnostic accuracy, efficiency, predictive modeling, personalized care, and data-driven decision-making.

*Correspondence. Md Mostafizur Rahman, Department of Biological Sciences, St. John's University, New York, USA
E-mail: md.rahman20@my.stjohns.edu

Editor Md Haroon Or Rashid, Ph.D, And accepted by the Editorial Board Jan 12, 2025 (received for review Oct 28, 2024)

1. Introduction

The effects of AI on the fields of economy, science, art, and even social life have been profound, and the transformation continues. In the area of medical diagnostics within laboratory medicine, the role of AI has grown increasingly significant due to the contributions of organizations promoting its adoption and regulation, along with its potential to enhance productivity and diagnostic accuracy. To keep pace with these critical advancements,

Author Affiliation.
[1] Department of Electrical & Computer Engineering, North South University, Dhaka, Bangladesh
[2] Department of Biochemistry and Molecular Biology, Tejgaon College, Dhaka, Bangladesh
[3] Burnett School of Biomedical Sciences, College of Medicine, University of Central Florida, Orlando, FL 32827, USA
[4] Department of Biological Sciences, St. John's University, New York, USA
[5] Department of Laboratory Medicine, Institute of Public Health, Dhaka, Bangladesh

Please cite this article.
Rahman, M. H., Biswash, M. A. R., Debnath, A., Siddique, M. A. B., Rahman, M. M., Hasan, M. M., Mou, M. A. (2025). "The Future of AI in Laboratory Medicine: Advancing Diagnostics, Personalization, and Healthcare Innovation", Journal of Primeasia, 6(1),1-6,10151

this review provides an integrated understanding of AI technology and its application in clinical and instrumental medicine. It also aims to facilitate discussions among the scientific community, professional associations, and policymakers regarding appropriate regulatory frameworks that ensure ethical and responsible use of AI, while highlighting the need for robust surveillance due to the complex nature of healthcare data management. (Ahmad et al., 2021).

Artificial intelligence (AI) is a research field dedicated to developing systems that can perform tasks requiring human intelligence. It includes varying levels of complexity and provides opportunities for applications that can significantly impact society, guided by ethical perspectives. The impact of AI on our society keeps increasing, especially through machine learning algorithms, which, although not a new concept, represent some of AI's most significant advancements. These algorithms extract underlying patterns from data, enabling systems not only to analyze data for decision-making and prediction but also to create and generate new knowledge through continuous learning from new data, which may be entirely or partially similar to previously processed data (Górriz et al.2020).

2. Fundamentals of Artificial Intelligence

The terms artificial intelligence (AI), machine learning (ML), and deep learning (DL) have become popular and are often used interchangeably. They lack strict definitions, and the distinction between them may depend on the educational background of the speaker. On the other hand, the underlying principles are not complex. (Moosavinasab et al.2021)

AI acts as the broadest concept here: the ability of a machine to perform tasks that usually require human intelligence. The term AI also refers to the practical implementation of such machines. Without relevant context, this term may include non-data related methods, for example, expert systems (Hassani et al.2020).

ML, which is a subset of AI. It is based on the concept of learning, where a program is provided with successively more complex input data, enabling the program itself to modify its parameters to better predict specific output results or to discover a previously unknown data structure. In most cases, this happens through important abstract data exchanges. Requirements, like the availability of a large-scale ground truth dataset, are generally less strict compared with other data-based models, such as, deep learning (Joshi et al.2024).

More specifically, the latter employs DL, a subset of ML. DL operates on a set of algorithmic models based on the learning of multiple layers of increasingly complex data extraction and transformation. It employs neural network layers and extends ML in terms of performance. Despite that, the requirements for the dataset and its processing, as well as for training, validation, and optimization steps, are much more precise and require considerable computational resources. (Dong et al., 2021)

3.Applications of AI in Laboratory Medicine

Many different applications of AI in laboratory medicine are conceivable and are being analyzed in clinical and biomedical research. AI applications can be performed either on data originating from clinical chemical analyses or on medical imaging data. While the use of AI in medical imaging is already further advanced, investigations of AI-supported decision support systems in clinical laboratory applications are beginning to be established. (Haymond and McCudden2021)

In the field of medical imaging, AI has become particularly popular through its acceptance with regard to diagnostic imaging (Table 1). The majority of recent research studies, review papers, and clinical initiatives have focused on the use of AI in the area of radiology, where great advancements have been made and a number of AI algorithms have already been approved for clinical use. Diagnostic imaging is a data-dense field and has received a lot of funding for AI research. Further clinical research applications have been established in the fields of anatomic and molecular pathology. In this review, we focus on AI applications in clinical laboratory medicine, which may support clinical decision-making and allow people to benefit from analyses of large, complex data sets from clinical chemistry and clinical biochemistry (Hussain et al.2022).

Artificial Neural Networks The identification of complex patterns in data constitutes one of the main functions of neural networks, which are emulative of the complex processing of human perceptions and cognitive processes. Although discussion of the surrounding terminology is ongoing, artificial intelligence is often employed as an umbrella term to cover machine learning, with its concepts of support vector machines, decision trees, and general statistical methods. Machine learning, in turn, is often used as an umbrella term for deep learning, which relies on the use of artificial neural networks. However, it is of note that each of the simultaneous concepts of AI, machine learning, and ANN can be used interchangeably without confusion of the terminology. However, this should only be done provided there is no requirement to highlight the workings of one over the other (Jakhar and Kaur, 2020).

3.1. Automated Image Analysis

Automated image analysis has been exploited to read CCA tests for over 30 years. The initial breakthrough came with the Serono Image Analysis System, designed to assess visually read latex agglutination tests, it was also easily adaptable for the agglutination methods used with enzymes and gold conjugated with specific serum antibodies. The principle underlying most CCA test image analysis methods is classified into the density of the T. solium antigens revealed by the metallic complex present over the lumen of the CCA strip.

Presently, most pioneers participating in the fight against the human immune system that detects T. solium are antigens found concentrated at various lumen localization-specific antigen sites (Adnan et al.2021).

These techniques rely directly on the ability to accurately isolate the lumen line where the control line ends, although they are also effective in identifying, counting, and recognizing the test line close to the line. However, we argue that the density of high antigen components is the most likely to be supported by positive test effects in specific anatomical regions of the region concerned. Conversely, image analysis technology is a cornerstone of viewing the human texture on the Immuno Cassettes strip; Histoquant methodology is applied to automatically locate numerous features and examine the resulting metrics and dynamics of histophenous (Bruni et al., 2020).

3.2. Diagnostic Decision Support Systems

Diagnostic rules are formulated based on the specific malignancy setting. These rules encompass general problems, such as that of distinguishing biologically benign from malignant, in the contextualized domain of a locus-specific clinical decision. Examples include the use of diagnostic rules to assist in the automated classification of the most prevalent subtypes in the differential diagnosis of malignant lymphoproliferative disorders using multiparametric flow cytometric immunophenotyping. With the development of new biochemical or molecular methods, diagnostic decision support systems are becoming more and more important. The disease-specific knowledge and expertise are propagated through various levels of presentation, enabling stepwise access to the expanding universe of interdisciplinary laboratory medicine. Structures for a telepathology infrastructure have been evaluated and are implemented to test the various concepts and to control the utility of the resulting tools in the daily clinical practice of pathology (Xu et al.2023).

Biomedical artificial intelligence and laboratory medicine together form the distinct fields of basic science and specialized engineering, often referred to as diagnostic decision support systems implemented in the domain of laboratory medicine. Laboratory tests which include multiple elements can be automated due to the development of multi-sample handling, microtechnology, and methods that are compatible with the organization of automated methods. Automated instrumentation can efficiently perform for simple and clear measurement procedures. For instance, at the pre-analytical level, advanced blood sampling systems may provide well-prepared samples that fulfill the requirements of modern analytical technology. (Akhtar, 2024)

3.3. Predictive Analytics

Predictive analytics methods use models derived from data and insights gained to anticipate future or otherwise unknown events. They provide estimates about uncertain future events, both those with present indicators and those currently unknown, potentially giving healthcare managers and providers the ability to weigh various choices. These models can indicate a future health care event such as the likelihood of a patient contracting a disease, a change in chronic condition, or experiencing an adverse clinical outcome up to several months in advance. Predictive modeling forms the basis of using information to predict future events, including the knowledge, desire, and ability for data extraction from many structured and unstructured data types within the healthcare field. Optimally performed predictive modeling can detect diseases in a preclinical stage, which can, in turn, lead to better treatment (Honkala et al.2022).

State-of-the-art electronic health record (EHR) systems provide a rich source of clinical anthropometric data, which is highly relevant for predictive modeling. Previous work has developed methods for extracting billing information, laboratory results, medications, and inferred conditions or illnesses from free-text data. More importantly, machine learning models can be trained to automatically detect the onset of various medical conditions from unstructured EHR data. EHR data have also been used in the predictive modeling of diseases, not only through traditional regression models but also with newer approaches capable of handling large, complex data and nonlinear relationships, such as neural networks and other forms of deep learning. In collaboration with commercial laboratories, EHR data have been integrated with complex diagnostic testing results, further enhancing the capabilities of personalized medicine (Amirahmadi et al., 2023).

4. Challenges and Limitations

Regulatory compliance, standardization, validation, risk assessment, and legal and ethical concerns present significant challenges for artificial intelligence (AI) strategies in clinical laboratory medicine. Laboratory algorithms, in particular, face most of these challenges related to regulatory frameworks, standardization, and validation. These frameworks categorize AI models into high, moderate, and low-risk levels, with stricter controls applied to higher-risk models to ensure patient safety. Clinical algorithms must undergo thorough validation on a broad scale to avoid the "black box" effect where the input and output data are known, but the underlying process or algorithm remains undisclosed. Many AI models used in translational research encounter similar challenges and limitations in managing risk. Additionally, AI routines often lack traceability, and results may be provided without proper documentation or support from the manufacturer. To transfer artificial intelligence algorithms into clinical use, there should be enough output evidence to convince people of their efficiency, performance, and robustness (Yanamala and Suryadevara; 2024).

Table 1: AI Applications in Laboratory Medicine

AI Application Area	Key Focus	Current Status	Example
Medical Imaging	Diagnostic imaging	Advanced, with clinical AI algorithm approvals	Radiology, Anatomic & Molecular Pathology
Clinical Laboratory Medicine	Data analysis and decision support	Emerging	Clinical chemistry, Biochemistry
Artificial Neural Networks (ANN)	Pattern identification and complex data processing	Evolving with machine learning	Decision trees, Support vector machines
Clinical Decision Support	Large, complex data set analysis	Developing	AI-assisted diagnostics

The performance of the model, or the risk of it showing bad behavior or bad population behavior, might drop when exposed to out-of-distribution data, fundamentally undermining their safety. Conversely, models might lack the capacity to learn how to confidently drive a classification with a threshold; that capacity is essential when a clinician is deciding what to do next and needs to have some confidence in the model's prediction. Thus, the risk management approach for AI models differs from that of risk assessment models used for biomarker selection in translational research. This difference stems from the inherent weaknesses of AI models. These challenges, along with methodological flaws and a lack of transparency, have prompted journals, institutions, and the emerging lab tech industry to establish guidelines, checklists, and validation processes for manuscripts involving translational models. In the future, the guidelines may be improved, but for now, they are sorely needed to ensure the validity, transparency, and applicability of AI in patient diagnosis and prognosis (Schuett, 2024).

5. Future Directions and Opportunities

Given the current state of AI approaches in laboratory medicine, the potential applications and benefits are virtually limitless. In the pre-analytical and analytical domains, the advantages of AI are being leveraged to enhance existing tools or develop new ones, such as automated image screening for pathological cells and microscopic disease diagnostics, data analytics of clinical testing which integrates medical big data, and bioinformatics analysis of next-generation sequencing data. AI-based clinical decision support systems, expert systems, or chatbots in personalized health care and laboratory management can empower clients to self-manage their health issues and thus enhance health in certain areas. Since aggressive behavioral phenotypes associated with particular genotypes can be discovered, laboratory animal testing can also benefit from AI. (Gruson et al., 2020)

Databases of patient information at the petabyte scale, analyzed in minutes by thousands of processors, have the potential to revolutionize diagnostics and disease management. Health insurance claims data can be mined to predict patient outcomes, while biomarker data can enhance diagnostic indicators for an expanding range of diseases. AI also offers significant promise in comparative effectiveness research and health economics, particularly in defining patient-centered diagnostic categories. In everyday clinical laboratory practice, AI extends physicians' cognitive capabilities by processing vast amounts of data to generate meaningful insights. Integrated diagnostics powered by AI could become a game-changer for personalized medicine. The possibilities of AI are immense, and those with the vision to harness these technologies for medical diagnostics stand to be richly rewarded. (Adler-Milstein et al., 2021)

6. Conclusion

Artificial intelligence (AI) has emerged as a transformative force in laboratory medicine, Providing unprecedented accuracy, efficiency, and personalization. Its integration into diagnostic processes allows earlier disease detection, more efficient use of resources, and more informed clinical decision-making. Despite significant advancements, challenges such as regulatory compliance, data standardization, ethical considerations, and transparency hinder broader adoption. Such challenges will require ongoing investment in AI research, interdisciplinary collaboration, and professional development to ensure the safety and effectiveness of AI technologies.

The transformative potential of AI reaches far beyond its current applications, envisioning a future where personalized medicine becomes the standard and diagnostic systems evolve into cognitive partners for clinicians. Building trust and refining AI models will empower laboratory medicine to harness its full capabilities optimizing healthcare delivery, enhancing patient outcomes, and driving groundbreaking medical innovation. The journey toward widespread AI adoption is a dynamic and ongoing process, informed by innovation, ethics, and collaboration.

Author contributions

M.H.R. and M.M.R. conceptualized and developed the methodology. M.A.R.B., A.D., and M.A.B.S. prepared the original draft and reviewed and edited the writing. M.A.M. and M.A.A. analyzed the data and reviewed and edited the writing.

Acknowledgment

None declared.

Competing financial interests

The authors have no conflict of interest.

References

Adler-Milstein, J., Chen, J. H., & Dhaliwal, G. (2021). Next-generation artificial intelligence for diagnosis: From predicting diagnostic labels to "wayfinding." JAMA. https://doi.org/10.1001/jama.2021.22396

Adnan, M. M., et al. (2021). Automatic image annotation based on deep learning models: A systematic review and future challenges. IEEE Access, 9, 50253–50264. IEEE. https://doi.org/10.1109/ACCESS.2021.3068897

Ahmad, Z., Rahim, S., Zubair, M., & Abdul-Ghafar, J. (2021). Artificial intelligence (AI) in medicine, current applications and future role with special emphasis on its potential and promise in pathology: Present and future impact. Diagnostic Pathology. Springer. https://doi.org/10.1186/s13000-021-01085-4

Akhtar, Z. B. (2024). Exploring Biomedical Engineering (BME): Advances within accelerated computing and regenerative medicine for a computational and medical science. J Emerg Med OA. Opast.

Amirahmadi, A., Ohlsson, M., & Etminani, K. (2023). Deep learning prediction models based on EHR trajectories: A systematic review. Journal of Biomedical Informatics. ScienceDirect. https://doi.org/10.1016/j.jbi.2023.104430

Bruni, D., Angell, H. K., & Galon, J. (2020). The immune contexture and Immunoscore in cancer prognosis and therapeutic efficacy. Nature Reviews Cancer. https://doi.org/10.1038/s41568-020-0285-7

Dong, S., Wang, P., & Abbas, K. (2021). A survey on deep learning and its applications. Computer Science Review. https://doi.org/10.1016/j.cosrev.2021.100379

Górriz, J. M., et al. (2020). Artificial intelligence within the interplay between natural and artificial computation: Advances in data science, trends and applications. Neurocomputing, 410, 237–270. ScienceDirect. https://doi.org/10.1016/j.neucom.2020.05.078

Gruson, D., Bernardini, S., Dabla, P. K., & Gouget, B. (2020). Collaborative AI and laboratory medicine integration in precision cardiovascular medicine. Clinica Chimica Acta. https://doi.org/10.1016/j.cca.2020.06.001

Hassani, H., et al. (2020). Artificial intelligence (AI) or intelligence augmentation (IA): What is the future? AI, 1(2), 8. MDPI. https://doi.org/10.3390/ai1020008

Haymond, S., & McCudden, C. (2021). Rise of the machines: Artificial intelligence and the clinical laboratory. The Journal of Applied Laboratory Medicine, 6(6), 1640–1654. https://doi.org/10.1093/jalm/jfab075

Honkala, A., et al. (2022). Harnessing the predictive power of preclinical models for oncology drug development. Nature Reviews Drug Discovery, 21(2), 99–114. https://doi.org/10.1038/s41573-021-00301-6

Hussain, S., et al. (2022). Modern diagnostic imaging technique applications and risk factors in the medical field: A review. BioMed Research International, 2022(1), 5164970. Wiley. https://doi.org/10.1155/2022/5164970

Jakhar, D., & Kaur, I. (2020). Artificial intelligence, machine learning and deep learning: Definitions and differences. Clinical and Experimental Dermatology. https://doi.org/10.1111/ced.14029

Joshi, G., et al. (2024). FDA-approved artificial intelligence and machine learning (AI/ML)-enabled medical devices: An updated landscape. Electronics, 13(3), 498. MDPI. https://doi.org/10.3390/electronics13030498

Moosavinasab, S., et al. (2021). DeepSuggest: Using neural networks to suggest related keywords for a comprehensive search of clinical notes. ACI Open, 5(1), e1–e12. Thieme. https://doi.org/10.1055/s-0041-1729982

Schuett, J. (2024). Risk management in the artificial intelligence act. European Journal of Risk Regulation. Cambridge. https://doi.org/10.1017/err.2023.1

Xu, Q., et al. (2023). Interpretability of clinical decision support systems based on artificial intelligence from technological and medical perspective: A systematic review. Journal of Healthcare Engineering, 2023(1), 9919269. Wiley. https://doi.org/10.1155/2023/9919269

Yanamala, A. K. Y., & Suryadevara, S. (2024). Navigating data protection challenges in the era of artificial intelligence: A comprehensive review. Revista de Inteligencia Artificial en Medicina, 15(1), 113–146. https://doi.org/10.4236/ojbm.2025.132037