DOI: 10.7860/JCDR/2026/79420.23151

Letter to Editor

Biochemistry Section

Machine Learning and Artificial Intelligence Model, Transforming the Future of Clinical Biochemistry: A Letter to Editor

ASTHA YADAV[1], JOEL SAM[2]

Keywords: Automated quality control, Digital diagnostics, Genomic interpretation, Laboratory efficiency, Predictive analytics

Machine Learning (ML) and Artificial Intelligence (AI) models are tools of modern computing innovation that are leading the way for revolution in changing the functioning of modern life. These digital tools help solve complex problems encountered even by advanced systems. This technology has started to be utilised in healthcare, where it helps in designing predictive models of diseases, diagnosis of patients and their prognosis. Clinical biochemistry has been the cornerstone of this advancement and has helped physicians make better treatment decisions. The introduction of AI and ML models into clinical biochemistry would bring significant changes in the way it functions [1].

With the advent of new technologies into healthcare, it is important to be cautious with regard to its implementation and usage. Several factors need to be kept in mind before the full-fledged use in day-to-day clinical life. Pre-analytical errors, such as mislabeling of samples in a laboratory, remain a major problem in clinical biochemistry. Conventionally, clinical laboratories were dependent on delta check to spot pre-analytical errors, but due to the increasing number of samples, these methods are often time-consuming and may be overlooked, often missed. The problems that we encounter with the usage of AI and ML models could be solved by newer models, such as Artificial Neural Network (ANN), which can identify mislabeled samples with an accuracy of around 92.1%, compared to human reviewers, which stand at 77.8% [2]. The utilisation of ANNs in clinical biochemistry reduces pre-analytical error thereby leading to better diagnosis and improved patient care.

Within analytical phase, AI can detect anomalies in quality control, identify trends, and predict Quality Control (QC) failures well in advance, thereby reducing the error rate in the system. ML models can monitor instrument signals and alert for drift calibration issue which in turns reduces the erogenous result. AI models can help in result interpretation, thereby providing a better insight for diagnosis of the disease. AI can reduce workload by auto-verification, ensuring that critical values are communicated to clinician for better patient outcome. Compliance to International Organisation for Standardisation (ISO) standards can be regulated by AI models; predictive models can ensure optimal reagent usage, thus reducing waste.

AI models can help create ideal condition for proper laboratory functioning, of the lab so as the integrity of the samples aren't compromised. Test turnaround time, reference ranges, test volumes, and machine workloads can all be predicted using machine learning [3].

Clinical laboratories using Patient-Based Real-Time Quality Control (PBRTQC) can detect even the slightest shift in analytic data by continuous monitoring. With respect to conventional quality control methods, AI-driven PBRTQC can detect deviation in real time, thereby protecting the operator from potential errors which could influence the result and subsequent clinical outcomes [4].

Building on these analytical advancements, AI and ML also offer significant benefits in the post-analytical phase. For instance, a previous study shown that ML model achieved a Down syndrome detection rate of 85.2% while maintaining a false positive rate of 5%, in comparison to conventional method. Same study showed that the triple test, which is incorporated in the second trimester, has a detection rate of 60-65% with the same false positive rate [5].

It is evident that the improvements in screening rates are attributed to the early detection of the disease which in turn lead to better-informed decision-making for the patients and healthcare providers.

The utilisation of conventional screening methods would invariably lead to a false positive result which would inflict undue stress on the patients and would force them to undergo follow-up tests [5]. This is where the random forest classifiers outperform conventional tests. The application of random forest classifiers in AI models enables precision analysis of metabolic markers, significantly reducing the false positive rate of inborn errors of metabolism. This includes conditions such as ornithine transcarbamylase deficiency (98%), very long-chain Acyl-CoA Dehydrogenase (ACAD) deficiency (2%), glutaric acidemia type 1 (89%), and Methylmalonic acidemia (MMA) (45%). The accuracy of Glutaric Aciduria Type 1 (GA-1) false positive rate using methods like Random Forest method was comparable to the Clinical Laboratory Integrated Reports (CLIR). This highlights the potential of incorporating newer technologies, such as machine learning, into newborn screening programs, thereby showing promising advancement in the field of biochemistry [6].

Online AI-driven tools are helping clinicians in interpreting results more efficiently, reducing diagnostic uncertainty, and improving decision-making. It is understood that the diagnosis of genome-based rare diseases has been associated with high costs for individual. Genome-based diagnostics of rare disease largely encompass the interpretation of patient clinically along with the genetic variants with respect to their phenotype. This area would greatly benefit from AI models, which have shown promising results by reducing the time taken for genomics interpretation. Predictive models would play a pivotal role in this as the information of the disease would invariably increase with due time. The performance of Fabric GEM, an AI tool, has helped us in genome interpretation and its expedition [7].

However, with any new tool, challenges are inevitable, and AI isn't new in that domain. The challenge of data privacy, ethical issues and transparency are always a threat for the implementation of new technologies. These important attributes must be built into the system so that trust among clinicians and healthcare professionals. Regulatory guidelines and reliability will need to be established in clinical decision-making [8].

AI should always be used as a supportive tool in healthcare, not as a replacement for the healthcare worker. The idea of any new technology should be to augment the existing systems and not merely be a replacement to increase speed and accuracy. If we can implement AI and ML models safely and sensibly into the system-ranging from screening to laboratory management and quality control-we could be in a position where it benefits the patient and the doctors. This could improve our overall lives and, most importantly, the accessibility of healthcare to all at a faster and affordable cost. The transformative power of AI would invariably shape the way we see the future of clinical biochemistry, provided the integration is thoughtful and patient-centered.

REFERENCES

[1] Mitra P, Gupta S, Sharma P. Artificial intelligence in clinical chemistry: Dawn of a new era? Indian J Clin Biochem. 2023;38(4):405-06.

[2] Farrell CJ. Identifying mislabelled samples: Machine learning models exceed human performance. Ann Clin Biochem. 2021;58(6):650-52.

[3] Bunch DR, Durant TJ, Rudolf JW. Artificial intelligence applications in clinical chemistry. Clin Lab Med. 2023;43(1):47-69.

[4] Lorde N, Mahapatra S, Kalaria T. Machine learning for Patient-Based Real-Time Quality Control (PBRTQC), analytical and preanalytical error detection in clinical laboratory. Diagnostics (Basel). 2024;14(16):1808.

[5] He F, Lin B, Mou K, Jin L, Liu J. A machine learning model for the prediction of down syndrome in second trimester antenatal screening. Clin Chim Acta. 2021;521:206-11.

[6] Peng G, Tang Y, Cowan TM, Enns GM, Zhao H, Scharfe C. Reducing false-positive results in newborn screening using machine learning. Int J Neonatal Screen. 2020;6(1):16.

[7] De La Vega FM, Chowdhury S, Moore B, Frise E, McCarthy J, Hernandez EJ, et al. Artificial intelligence enables comprehensive genome interpretation and nomination of candidate diagnoses for rare genetic diseases. Genome Med. 2021;13(1):153.

[8] Boudi AL, Boudi M, Chan C, Boudi FB. Ethical challenges of artificial intelligence in medicine. Cureus. 2024;16(11):e74495.

PARTICULARS OF CONTRIBUTORS:

1. Senior Resident, Department of Biochemistry, Dr. D. Y. Patil Medical College, Hospital and Research Centre, Dr. D.Y. Patil Vidyapeeth, Pune, Maharashtra, India.
2. Junior Resident, Department of Preventive and Social Medicine, Armed Force Medical College, Pune, Maharashtra, India.

NAME, ADDRESS, E-MAIL ID OF THE CORRESPONDING AUTHOR:
Astha Yadav,
Sunshree Kangan Apartment, NIBM Road, Pune-411048, Maharashtra, India.
E-mail: asthayadav2007@gmail.com

PLAGIARISM CHECKING METHODS: [Jain H et al.]

- Plagiarism X-checker: Apr 06, 2025
- Manual Googling: Sep 18, 2025
- iThenticate Software: Sep 20, 2025 (8%)

ETYMOLOGY: Author Origin

EMENDATIONS: 6

AUTHOR DECLARATION:

- Financial or Other Competing Interests: None
- Was informed consent obtained from the subjects involved in the study? NA
- For any images presented appropriate consent has been obtained from the subjects. NA

Date of Submission: **Mar 17, 2025**
Date of Peer Review: **Jul 02, 2025**
Date of Acceptance: **Sep 22, 2025**
Date of Publishing: **Apr 01, 2026**