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Artificial Intelligence in Medical Biochemistry Laboratories: From Automation to Clinical Decision Support

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***Abstract*— Medical biochemistry laboratories are being rapidly transformed from rule-based automation environments into intelligent diagnostic ecosystems by artificial intelligence. Integration of Natural language processing, deep learning, machine learning, and expert systems and emerging agentic AI models across pre-analytical, analytical, and post-analytical laboratory workflows is highlighted in this review. Automated quality control monitoring, predictive maintenance of analysers, intelligent sample routing, auto verification of results, multimodal data interpretation, and enhanced clinical decision support are included among the unique contributions of AI in laboratory medicine. Further discussion is provided in the article on AI's contribution to increased diagnostic precision, turnaround time and operational efficiency. Obstacles pertaining to model interpretability, data quality, regulatory compliance, and workforce adaptation are addressed. Ethical considerations, data privacy safeguards, and governance requirements for AI deployment in laboratory settings are also outlined. Artificial Intelligence is not positioned as an alternative for laboratory experts, but instead presented as decision-support partner through which precision, safety, and clinical value in modern biochemistry services are enhanced.**

***Index Terms*— Artificial Intelligence, Natural Language Processing, Medical Biochemistry, Laboratory Automation, Deep Learning, Clinical Decision Support System, Machine Learning.**

I. INTRODUCTION

In medical diagnostics, AI has emerged as a game changing technology that improves the interpretation of complex clinical data and helps with accurate and efficient illness diagnosis decision-making.(1) Artificial intelligence (AI) has steadily improved in utility and dependability for a variety of uses, especially in the healthcare sector. It has ability to improve clinical practice, which would improve patient care and results, by promoting more organisation and efficiency. (2) Artificial intelligence (AI), according to John McCarthy, is "The science and engineering of making intelligent machines." After beginning as straightforward set of "If, then order, artificial intelligence has grown over time to incorporate increasingly intricate formula that function similarly to human brain. (3) Reaching the quadruped aim of healthcare, raising patient and companion, improving population health, and concentrating on efficiency, reduction of expenses and value based development in healthcare systems worldwide.

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One potential solution to some of these supply and demand issues is use of technology and artificial intelligence in the health sector. (4) Technological progress in mobile, internet of things, computational power, data security along with growing availability of multi-modal data, signals a turning point in the relationship between healthcare and technology. (5)

ML and non-ML approaches are both included in AI technology in healthcare. Machine learning, a branch of artificial intelligence, employs procedures to evaluate datasets that are crucial for training, testing, and evaluating ML models across tasks such as classification, regression, computer vision, and natural language processing.(6)

Non-ML techniques, on the other hand, concentrate on analysis and prognosis without the use of adaptive algorithms and rule based models and conventional statistical techniques. (7)

In pathology, this limitation is now being overcome and diagnostic precision is being improved using computational methods. The initial step in computer evaluating data is provided by digital imaging, and a more advanced and widely adopted method in the field is represented by whole-slide imaging. (8) The processing of dynamic images is enabled by whole-slide imaging and more consistent results than those obtained with standard camera-based digital imaging approaches are provided. (9)

A particularly revolutionary impact is being observed in the laboratory setting as a result of this progress. Instead of being static testing settings, agentic AI may change laboratory environments into adaptable, robust, and dynamic systems.(10) It facilitates intelligent workflow modifications, real-time decision-making, and changing operational strategies by placing a strong emphasis on adaptability, malleability, and ongoing learning.(11)This goes beyond conventional automation and passive data reporting in favour of continuous, self-optimising laboratory processes, which is consistent with the ideas of complex adaptive systems and adaptive management.(12)

Consider, for example, the shared objective of releasing a troponin result in a timely and safe manner an agentic AI could independently examine the data management systems, intermediary software, digital health records, fetch instrument status, archival records, and protocol, route of the sample through complete automated liquid handling, apply test use rules, validate and generate structured reports, interpret results with recommendations for follow-up and develop abnormal findings to staff. (13)

Computer vision is the process of gathering, examining, and processing images and video, including face recognition. Robotics applications are diverse and include autonomous vehicles, command structures, detectors, and programming (e.g., robotics liquid handling). Pro systems depend on knowledge of humans to derive rules from processes, such as if/they/else rules for complex decision making. Lastly, machine learning encompasses wide range of algorithm development techniques for categorisation, grouping, and prediction.(3)

The utilisation of AI in healthcare practice and research progressed rapidly. In laboratory medicine, large language models (LLMs) and machine learning applications have demonstrated potential in diagnosis, clinical decision support, and process improvement.

Even though these AI systems are capable of producing insightful analysis and suggestions, human users are still required to evaluate and apply their results.(13)

Creating machines can perform activities that need human intelligence aim of artificial intelligence fast growing field of computer science. Artificial intelligence includes machine learning, deep learning, natural language processing and other methods. Big Language Models are family of artificial intelligence process that understand, summarise, create, and predict new text-based material using deep learning methods and incredibly massive data sets.

A wide range of NLP activities, such as text generation, translation, content summarisation, rewriting, classification, categorisation, and sentiment analysis, can be performed by LLMs, which are designed to produce text-based content.(14)

A. Artificial Intelligence Technologies in Laboratory Medicine

AI is quickly becoming a cornerstone of research and healthcare practices. Large language models and machine learning applications in laboratory medicine have already demonstrated promise in process optimization, clinical decision support, and diagnosis.(15) These AI systems still require human users to comprehend and use their outputs, even though they are capable of producing strategies, foresight, and instructions.(16)

The integration of multiple modalities is another area. The management of several layers of data, such as genomics, proteomics, and metabolomics and exposome data is becoming a greater challenge for laboratory medicine. This variability is frequently found to be difficult for traditional AI models to handle, but complexity is managed by agentic AI through the finding of literature, the connecting of datasets, and the production of adaptive insights. (17)

B. Laboratory Applications of Machine Learning

There are several possibilities to use machine learning across all laboratory specialities, several of which regulatory taken agreement for utilisation of clinical diagnosis. Because applications of machine learning to recognise clinical groups at risk for poor results or to assist with comorbidity and prognostication typically do not develop from laboratory or inform their judgments, they are not included in the examples in this section.(18) Since various patient level risk prediction models use manufactured derivatives of either laboratory data features, these apply to other sections of the review. Here, we concentrate on instances that seek to raise the calibre and effectiveness of clinical laboratory operations and services.(19)

C. Deep Learning Applications in Laboratory

ML includes deep learning (DL) as a subfield. It imitates human brain's complex neural networks. A process that learns from input data by using layers of interconnected nodes called neurons. Deep Learning used in radiomics, which is the process of finding practical significance patterns in human data that are invisible to the human eye.(20) Clinical laboratories and the medical profession are the main applications of AI and ML for structured data. Natural language processing, neural networks, current deep learning, and traditional SVM have all been used to process unstructured data such as clinical notes and patient reports is involved in the origination, perception and categorisation of medical records and analysing capturing patient interactions, creating reports, and taking unstructured clinical notes.(21)

D. Natural Language Processing

Perhaps no branch of artificial intelligence has as much excitement, hope and history as Natural Language Processing. On the surface, someone who is unfamiliar with the subject might question why very young newborns are able to learn it with such ease. Even basic orders appear to be easy for many domesticated animal types to learn. Furthermore, many "everyday people" who have lived close to multilingual national borders for centuries, such as the majority of Europe, have seemed to have little trouble learning and mastering many languages. Natural human languages contain very rich and subtle distinctions, some of which are only understood by the context of the message or characteristics of the local language itself. (22) While machine learning and deep learning models primarily keep up pattern recognition and prediction tasks, agentic AI extends functionality by coordinating multiple systems and executing multi step laboratory processes. Outputs generated from these AI layers ultimately feed into Clinical Decision Support Systems (CDSS), where laboratory data are translated into clinically actionable insights. Thus, AI in laboratory medicine forms a continuum from data processing and automation to clinical interpretation and decision support. (23)

E. Clinical decision support systems (CDSS)

CDSS serve as watchdogs or advisors to support doctors, patients, and other users. The best practice for discharge of patients after surgery may be recommended by the CDSS as part of its advisory role. To guarantee the greatest results, this could involve recommended drugs and dosages, physical culture, frequent investigative exams and tests.(24) In addition to aiding with the best escalation and treatment of emergent consequences, most safely and economically feasible, CDSS can support patients in choosing alternative therapies or rehabilitation options.(25)

Medical errors, especially patient error can be significantly reduced with the help of CDSS.

Medication error modules are common feature of EHR software systems that help to protect patients. These CDSS will look for potential drug interactions with existing treatment plans, match prescribed medications to known patient allergies and recommend more cost effective or superior medication solutions.(26)

Practitioners, hospital administrators and practice managers can all benefit greatly from CDSS. For example, doctors and nurses may add or change guidelines to help them implement new standards and regulations.(22)

QA and QC in Artificial Intelligence:

In clinical laboratories, Artificial Intelligence becoming more and more essential to quality assurance (QA) and control (QC) procedures, providing improvements in patient safety, operational efficiency and diagnostic precision.(27) By evaluating massive real-time datasets to detect patterns, abnormalities and departures from predetermined protocols or thresholds, AI systems are excellent for keeping an eye on laboratory activities. (28) Machine learning algorithms for instance, are able to identify minute variations in test results or instrument performance that can point to possible problems with quality control, including reagent deterioration, calibration mistakes or a change in the laboratory environment. (29)

Reduced risk of decreased diagnosis accuracy and preventative laboratory equipment maintenance, a crucial part of modern QC frameworks are facilitated through early detection, as timely interventions are enabled. Predictive maintenance defined as the use of Using AI models to analyze equipment performance data and spot patterns that could point to upcoming problems or failures.(30) Unnecessary downtime can be prevented and consistent quality in test results can be ensured when maintenance requirements are anticipated. It has been shown through research that operational disruptions can be reduced and the longevity of laboratory equipment increased by AI-driven predictive maintenance systems.(31)

To minimize risks and optimize advantages, strong quality assurance and quality control frameworks are required for deployment of AI-driven systems. In order to guarantee AI tools' safe application in healthcare environments, the significance of context-specific quality assurance methods, such as acceptance testing prior to clinical deployment, ongoing QC monitoring and thorough user training is emphasized.(32)

II. AI in Post-Analytical Phase

A. Automated Result Validation

Auto verification methods have significantly increased the productivity of laboratories. The well-established rule-based auto verification models have drawbacks, though. The machine learning (ML) technique has special benefits for assessing big datasets. We looked into the usefulness of machine learning (ML) techniques for creating an autoverification system for artificial intelligence (AI) to facilitate laboratory testing. The algorithm model's precision and effectiveness were also confirmed.(33)

B. Interpretation of Biochemical Profiles

Clinical endocrine practice may eventually change as a result of the application of AI/ML to more accurately diagnose endocrine disorders, potentially prevent needless investigations, lower healthcare costs and improve digital storage of massive patient data, whether it be individual profile or composite data planning and observational study. Artificial intelligence diabetes management technologies, such artificial pancreas, are already a reality.(34)

Academic institutions and IT sector must make significant efforts to advance AI/ML technology in endocrinology. Endocrinologists ideally qualified to contribute significantly to the development of AI and ML.(35)

C. Critical Value Management

There is a chance to increase the efficiency of laboratory critical values (CVs) notification procedures. A crucial value or test is one "that requires immediate communication of results," as defined by The Joint Commission.The CV has been rejected by joint commission because it is a "test result that is significantly outside the normal range and may represent life-threatening values."(13) Critical Values must be reported to TJC as soon as possible, together with documentation indicating who received the results. The percentage of Critical value results with documentation indicating that caregivers have been informed of results is required by the College of American Pathologists standard.(35)

III. Future Perspectives

Future medical biochemistry laboratories are likely to transform into intelligent, semi-autonomous systems where explainable artificial intelligence supports transparent decision-making and enhances clinician trust.(36) The integration of digital twins will enable real-time simulation and optimization of laboratory workflows, while AI-enabled point-of-care testing will facilitate rapid, decentralized diagnostics.(37) Furthermore, combining biochemical data with genomics and multi-omics information will advance precision medicine, enabling more personalized, predictive, and preventive healthcare approaches.(36)

IV. Ethical, Data Privacy, and Regulatory Considerations

Important ethical and governance issues are raised by the adoption of AI in medical biochemistry laboratories. Strict de-identification, secure storage, and compliance with health data protection regulations are required for patient data used in AI model training.(37) Diagnostic equity may be affected by algorithmic bias if representative training datasets are not used. Transparency and clinical accountability are challenged by the "black-box" nature of some AI models.(38) Increasingly, clinical validation, performance monitoring, and explainability are required by regulatory bodies before the approval of AI tools. Structured oversight frameworks, continuous auditing, and human-centred AI must therefore be implemented to ensure safe and responsible AI integration.(39)

TABLE I: AI TECHNIQUES IN MEDICAL BIOCHEMISTRY

AI Technique	Core Principle	Key Applications in Medical Biochemistry Laboratories	Major Benefits	Limitations and Challenges
Learning from Machines (ML)	Statistical models are used by algorithms to identify trends in structured data.	•Prediction of biochemical risk markers •Disease risk stratification (diabetes, CVD, CKD) •Test result pattern recognition • Quality control trend analysis	• Handles large laboratory datasets •Improves diagnostic accuracy •Identifies hidden correlation •Supports predictive analytics	• Requires high-quality labelled data • Model bias from non-representative datasets •Limited interpretability in complex models
Deep Learning (DL)	Multi-layer neural networks automatically extract features from complex data	• Interpretation of electrophoresis patterns •Digital pathology–biochemistry integration •Automated anomaly detection in analysers •Image-based urinalysis	•High performance in complex, high-dimensional data •Reduces manual interpretation errors •Learns features without manual engineering	•Computationally intensive •“Black-box” decision process •Requires large training datasets
Natural Language Processing (NLP)	Analysis of unstructured textual data using language models	• Extraction of lab data from electronic health records (EHRs) •Automated report generation •Clinical decision support integration	•Converts unstructured data into usable information •Enhances documentation efficiency •Supports real-time clinical insights	•Language ambiguity issues •Requires domain-specific training • Privacy and data governance concerns
Expert Systems (Rule-Based AI)	Decision-making using predefined clinical rules and knowledge bases	• Reflex testing algorithm • Critical value alerts • Interpretation of liver/thyroid function panels	•Transparent decision logic •Easy integration with LIS •Clinically explainable outputs	•Limited adaptability •Cannot learn from new data •Requires continuous rule updates
Artificial Neural Networks (ANNs)	Brain-inspired network of interconnected nodes for nonlinear modelling	• Estimation of GFR, HbA1c trends •Multivariate disease prediction •Sepsis biomarker panels	•Captures nonlinear relationships •High predictive power • Useful for multi-marker analysis	• Overfitting risk •Difficult to interpret clinically • Needs expert tuning
Reinforcement Learning (RL)	Systems learn optimal actions through feedback and reward mechanisms	• Optimisation of analyser workflow •Intelligent sample routing •Laboratory process automation	•Improves operational efficiency •Dynamic adaptation to workload •Reduces turnaround time	•Complex to implement •Needs real-time feedback data • Limited current clinical validation
Computer Vision	Image analysis using AI for visual pattern recognition	•Automated blood smear analysis •Urine sediment examination •Gel electrophoresis interpretation	•Reduces observer variability •Speeds microscopic analysis •Enables digital archiving	•Requires standardised imaging •Performance affected by poor image quality •Validation required for clinical use

V. CONCLUSION

A transition from conventional automation to intelligent, data-driven diagnostic support systems is being enabled in medical biochemistry laboratories through artificial intelligence. Analytical quality, operational efficiency, and clinical interpretation are enhanced by AI, and the laboratory’s role in patient-centred care is thereby strengthened.

However, robust clinical validation, standardized data infrastructure, explainable algorithms, regulatory oversight, and continuous training of laboratory professionals are required for sustainable implementation. Ethical, safe, and effective integration of AI will be ensured by addressing these factors, and laboratory medicine will be positioned as a central contributor to precision and evidence-based healthcare.

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