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A Brief Discussion on the Theory and Application of Artificial Intelligence in Medical Diagnostics

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Abstract

In this new era of rapid technological advancement, Artificial Intelligence (AI) has achieved comprehensive, multi-level development. AI is simultaneously advancing across algorithms, computing power, and data, propelling medical testing from "digitalization" to "digital intelligence". Technological Level: Deep learning, federated learning, and multimodal fusion have reshaped the entire workflow—from sample preprocessing and feature extraction to quality control and result interpretation—forming a self-iterating knowledge-decision loop. Automated testing models, continuously trained on datasets exceeding one million annotated samples, simultaneously enhance sensitivity, specificity, and reporting timeliness. Application Dimension: AI has been embedded into core scenarios such as cytomorphology, mass spectrometry analysis, gene sequencing, and immunochromatography, enabling real-time "human-machine collaboration" decision-making. Leveraging edge computing, it extends tertiary hospital diagnostic capabilities to county-level facilities. Innovation Dimensions: Small-sample transfer learning, explainable algorithms, and dual-loop feedback mechanisms between laboratory and clinical data are addressing three major bottlenecks: data heterogeneity, scarce annotations, and causal traceability. This paper systematically outlines the technical foundations and practical applications of AI in medical laboratory testing, explores its innovative developments and challenges, and concludes with a vision for new pathways where AI can empower medical laboratory science.

Keywords

Artificial Intelligence, Medical Laboratory Testing

1. Introduction

Medical laboratory testing serves as the cornerstone of modern healthcare systems. Through standardized methodologies, it systematically identifies threats to human health, providing objective evidence for disease diagnosis, treatment efficacy monitoring, and prognosis assessment [1]. With continuous technological advancement, Artificial Intelligence (AI) is emerging as a core driver of innovation in medical testing. Deep learning-based pathological image analysis systems eliminate human interpretation bias, while data fusion from multiple centers within federated learning frameworks significantly enhances the detection rate of rare disease biomarkers. Concurrently, reinforcement learning algorithms optimize mass spectrometry workflows, boosting sample processing throughput [2].

Against this backdrop, Akhil Kondepudi's research team developed FastGlioma, an AI-based diagnostic tool [3]. FastGlioma integrates Stimulated Raman Histology (SRH) technology, a rapid, label-free optical imaging method with submicron resolution. Unlike traditional staining techniques, SRH imaging directly generates images based on a sample's biochemical properties, eliminating the need for dyes or markers. This enables real-time imaging during surgery, significantly reducing the time from sampling to obtaining results. Additionally, Jiang *et al.* proposed ROAM, an AI model for precise pathological diagnosis based on large Regions of Interest (ROIs) and pyramid transformer technology. ROAM effectively extracts multi-scale information from pathological images, enabling accurate diagnosis across multiple classification tasks, including glioma detection, subtype classification/grading, and molecular feature prediction [4].

These research findings demonstrate that AI, leveraging its robust learning and recognition capabilities, can automatically adjust dynamic thresholds and issue alerts for outliers, thereby enhancing the clinical relevance of test results. This digital transformation—combining algorithms, computing power, and data—is reshaping the entire medical testing process, from sample preprocessing to report interpretation. It is driving the shift from an experience-based model to a data-driven approach in medical testing, providing real-time, traceable decision support for precision medicine.

2. The Technical Foundation of AI-Assisted Medical Testing

AI is the science of enabling machines to think, learn, reason, and solve problems like humans. Among these, AI technologies such as machine learning and deep learning are the core technologies driving medical testing into a new era. The massive data analysis and intricate logical connections involved in medical testing require processing through artificial intelligence. Therefore, solving medical testing problems requires support from numerous models. Clear logical foundations can be addressed using logistic regression, while decision trees and random forests excel at handling auxiliary interactions between features and offer strong model interpretability. XGBoost/LightGBM possess powerful tabular data processing capabilities, significantly reducing time and effort expenditure. Support vector machines demonstrate outstanding performance with small samples and multidimensional data. In deep learning, Convolutional Neural Networks (CNNs) excel at processing unstructured data like images, sequence data, and waveforms. Recurrent Neural Networks (Transformers) handle sequence data, analyzing connections across different datasets. Autoencoders are used for dimensionality reduction and detecting abnormal results. The comprehensive, multi-level development of AI provides a solid foundation and a broad future for medical laboratory technology [5].

In summary, medical testing requires AI's capabilities in recognition and classification, as well as its ability to process high-dimensional and complex data. Therefore, we expect AI to engage in deep reasoning and rigorous induction when addressing problems, ultimately establishing a system that digitizes biological phenomena and employs computational models for learning. This approach will realize practical value in the field of medical testing. Furthermore, automation and intelligent features can optimize testing workflows, enhance the accuracy of disease early warning and medical decision-making, and bring about a paradigm shift in the medical testing domain.

3. Theoretical Foundations and Applications of AI in Medical Laboratory Practice

The application of AI in medical testing truly demonstrates its practical value. Artificial intelligence plays an extraordinary role in establishing various testing methods. In auxiliary diagnosis and disease risk assessment, ML models can integrate patients' past medical records, correlate them with previous conditions, and conduct comprehensive risk analysis of the patient's physical state, enabling early screening and early warning. In automating laboratory processes, Natural Language Processing (NLP) models handle vast datasets efficiently, significantly boosting productivity and reducing workforce strain. They enable automated microscopy, while machine learning models assess the reliability of test results, facilitating intelligent review. For result interpretation and predictive analysis, ML models analyze historical test data and demographic information to forecast patient outcomes, enabling timely and appropriate early interventions [6].

The impact of AI in medical laboratory testing is comprehensive and thorough, providing end-to-end support throughout the entire testing process. By employing AI for efficient problem-solving, it fundamentally ensures result stability. Applications vary across different laboratory disciplines. Clinical laboratory testing, the domain where AI demonstrates its greatest proficiency, exhibits exceptional capabilities: Hematology analysis achieves sensitivity far surpassing manual methods; urinalysis delivers standardized, quantitative reports; microbiology testing enables intelligent plate reading and accurate MIC interpretation, minimizing human error; mass spectrometry identification assists in precise pathogen identification; AI analysis of microbial genes provides direct clinical guidance for antimicrobial resistance prediction and drug selection [7]-[9].

In pathology, where pathological findings serve as the standard for disease management, AI will become a powerful assistant in applying pathological principles. For cancer diagnosis and classification, AI can precisely quantify tumor proportions to enable grading and staging. It enhances diagnostic accuracy for identifying micrometastases. In immunohistochemical quantitative analysis, AI evaluates key biomarkers such as HER2, PD-L1, and Ki-67, yielding more direct and accurate results. In renal pathology screening, AI excels at examining and marking specific cells, ensuring consistency in selection and accurately reflecting the patient's current physical condition [10]. For example, Edelmers *et al.* focus on developing and validating an AI model using U-Net architectures for the accurate detection and segmentation of spinal metastases from CT images, addressing both osteolytic and osteoblastic lesions [11]. The model demonstrated strong performance in vertebra segmentation, achieving Dice Similarity Coefficient (DSC) values between 0.87 and 0.96. For metastasis segmentation, the model achieved a DSC of 0.71 and an F-beta score of 0.68 for lytic lesions but struggled with sclerotic lesions, obtaining a DSC of 0.61 and an F-beta score of 0.57, reflecting challenges in detecting dense, subtle bone alterations.

Medical imaging plays an extraordinary role in disease prediction, screening, and treatment evaluation, offering proficiency and endurance surpassing human capabilities. Given the overwhelming volume of data processed in medical imaging departments, AI's intelligence and automation demonstrate significant advantages. Lesion detection and delineation can precisely map tumor boundaries through CT and MRI scans, enabling meticulous planning for subsequent radiation therapy. Within genomics and molecular diagnostics, AI serves as an indispensable assistant in processing vast amounts of high-dimensional data, progressively mitigating threats to human health and safety. By advancing hospital digitization, reducing healthcare disparities between urban and rural areas, and enhancing public well-being, AI fulfills its societal value [12].

4. Challenges and Recommendations for Artificial Intelligence in Medical Laboratory Testing

Technological advancements are rapidly evolving, with AI capabilities achieving a qualitative leap. However, significant limitations persist when applying AI to medical diagnostics. Challenges include the substantial professional investment required for model training and the scarcity of classic, accurate sample cases—particularly rare ones. To overcome these detection barriers, we can edit raw blood smear data by combining abnormal data with corresponding diseases into recognizable patterns for AI learning. This approach expands the dataset while establishing rigorous data cleansing, standardization, and quality control processes, thereby enhancing the quality and accuracy of AI-assisted detection [13].

Due to considerations of patient privacy and data security, hospitals face challenges in achieving large-scale sharing and aggregation of medical data for large language models, which may result in insufficient generalization capabilities [14].

Differences in machine debugging environments and parameters can cause inconsistent test results for the same model and sample across multiple runs, with even greater discrepancies observed between institutions. Therefore, establishing a unified platform for data integration and system standardization is essential. This approach enhances model generalization and adaptability by strengthening external validation and robustness training. Integrating equipment from diverse regions improves generalizability, mitigates the impact of specific conditions, and increases user acceptance of this technology.

Federated Learning inherently aligns with decentralized scenarios through its "data stays put, models move" approach, enabling model training directly on privacy-sensitive multi-party data. Its core mechanism and privacy protection design are as follows: Local computation + global aggregation; Each participant (client) trains models only on local data, uploading parameter updates rather than raw samples; Central nodes (or decentralized networks) solely perform aggregation (e.g., FedAvg weighted averaging), then distribute the global model back to clients—ensuring raw data never leaves its domain; Decentralized communication structure: To eliminate single points of failure and mitigate "central server malice" risks, fully Peer-to-Peer (P2P) topologies can be adopted: Clients exchange gradients or model fragments pairwise, then approximate the global optimum via gossip/consensus algorithms; Cryptographic enhancements: Homomorphic encryption/secret sharing: Parameters are aggregated in encrypted form, preventing any party from viewing others' plaintext updates. Even compromised aggregation nodes cannot reconstruct private information. Differential privacy and noise mechanisms: Clients add calibrated noise to gradients before uploading, or servers perform differential privacy pruning post-aggregation. This provides a quantifiable privacy budget ε against attacks like "member inference" or "model reverse engineering", significantly reducing side-channel leakage risks.

In zero-tolerance scenarios like medical testing, the black-box nature of algorithms is magnified to extreme levels. Algorithms deliver negative or positive results yet refuse to disclose any reasoning pathways. Physicians cannot map the unnameable "internal logic" to textbook-level evidence chains, rendering even the highest accuracy rates incapable of delivering that moment of certainty when the pen signs the discharge order. The shortest path to resolving this dilemma is translating the model into a "transparent file" that physicians can review, question, and archive. Specifically: Implement explainable AI frameworks to generate visual heatmaps and symbolic rule chains alongside each inference. Translate "neuronal activation" into clinical terms like "proportion of nuclear fission-like nuclei ≥ 3/HPFS and Ki67 > 20%", automatically compiling these into a one-page explanatory summary appended to reports. Simultaneously deploy continuous monitoring modules to push real-time sensitivity, specificity, and confidence drift metrics of the model on actual samples to the quality control dashboard. Trigger retraining and manual review immediately upon deviation from preset thresholds. Replacing "algorithm assertions" with explainable evidence and substituting "permanent deployment" with continuous monitoring transforms opaque, untrustworthy outputs into traceable diagnoses that physicians can confidently sign off on and patients can understand.

An invisible gap still exists between frontline clinicians and AI-assisted systems [15]. Report formats, workflow nodes, and operational habits remain incompatible, forcing doctors to jump between screens—time that should be saved is instead swallowed by extra steps. To truly integrate humans and machines into a cohesive team, training must become routine rather than a one-off lecture. The system's reasoning process within real cases must be laid bare, allowing physicians to witness firsthand how it uncovers overlooked clues. Trust will then gradually grow with each daily click. Simultaneously, streamline interfaces to two-step simplicity like smartphone photography. Integrate result notifications, critical value alerts, and retrospective queries onto a single page—eliminating extra windows and redundant entries. Make the AI assistant as accessible as a stethoscope, seamlessly woven into every action: rounds, image review, and documentation. Transform "usage" into second nature, and "assistant" into "teammate" [16].

In a social environment where collective honor runs deep, any medical error is magnified into a challenge to the entire team. When an intelligent system delivers an erroneous conclusion leading to an incident, if the boundaries of responsibility remain unclear, developers, hospitals, and physicians will become entangled in a stalemate of mutual blame. Legislation must first explicitly classify systems as "auxiliary tools", ensuring decision-making authority and signing rights remain solely with licensed physicians. Consequently, civil and even criminal liabilities should be attributed to the signatory, establishing a clear "primary responsible party" at the end of the medical chain. Simultaneously, algorithms trained with precision on mainstream populations may still exhibit inaccuracies among minority groups due to differences in skin tone, ethnicity, or geography, inadvertently widening health disparities. Therefore, "fairness" must be embedded into the data collection process: actively recruiting participants with diverse genetic backgrounds and living environments, using statistical methods to detect and correct sample imbalances, and subjecting models to "fairness audits" before deployment. This ensures potential biases remain in the laboratory rather than reaching the bedside. Only by advancing both accountability and data fairness in parallel can intelligent assistance truly become a "second pair of eyes" that physicians dare to use and patients dare to trust.

5. Conclusion

The rapid advancement of artificial intelligence in the new era has ushered in a transformative revolution in medical diagnostics. With a solidifying technological foundation and increasingly unlocked potential, AI is shifting from theoretical development toward large-scale clinical implementation. Although significant challenges remain in data management, ethical considerations, and clinical application, ongoing technological innovation and interdisciplinary collaboration will soon establish a secure, stable, and trustworthy AI ecosystem. This ecosystem will achieve the perfect integration of technical feasibility, clinical utility, and ethical legitimacy. This will propel artificial intelligence into becoming the most capable assistant in medical laboratory testing.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Zhang, S.M. (2018) Application and Prospects of Artificial Intelligence Technology in Medical Laboratory Science. *International Journal of Laboratory Medicine*, **39**, 513-516+520. (In Chinese)

[2] Delavy, M., Cerutti, L., Croxatto, A., Prod'hom, G., Sanglard, D., Greub, G., *et al.* (2020) Machine Learning Approach for Candida Albicans Fluconazole Resistance Detection Using Matrix-Assisted Laser Desorption/Ionization Time-of-Flight Mass Spectrometry. *Frontiers in Microbiology*, **10**, Article 3000. https://doi.org/10.3389/fmicb.2019.03000

[3] Kondepudi, A., Pekmezci, M., Hou, X., Scotford, K., Jiang, C., Rao, A., *et al.* (2024) Foundation Models for Fast, Label-Free Detection of Glioma Infiltration. *Nature*, **637**, 439-445. https://doi.org/10.1038/s41586-024-08169-3

[4] Jiang, R., Yin, X., Yang, P., Cheng, L., Hu, J., Yang, J., *et al.* (2024) A Transformer-Based Weakly Supervised Computational Pathology Method for Clinical-Grade Diagnosis and Molecular Marker Discovery of Gliomas. *Nature Machine Intelligence*, **6**, 876-891. https://doi.org/10.1038/s42256-024-00868-w

[5] Torkamani, A., Andersen, K.G., Steinhubl, S.R. and Topol, E.J. (2017) High-Definition Medicine. *Cell*, **170**, 828-843. https://doi.org/10.1016/j.cell.2017.08.007

[6] Pattilachan, T.M., Christodoulou, M. and Ross, S. (2024) Diagnosis to Dissection: AI's Role in Early Detection and Surgical Intervention for Gastric Cancer. *Journal of Robotic Surgery*, **18**, Article No. 259. https://doi.org/10.1007/s11701-024-02005-6

[7] Demir, R., Koc, S., Ozturk, D.G., Bilir, S., Ozata, H.İ., Williams, R., *et al.* (2024) Artificial Intelligence Assisted Patient Blood and Urine Droplet Pattern Analysis for Non-Invasive and Accurate Diagnosis of Bladder Cancer. *Scientific Reports*, **14**, Article No. 2488. https://doi.org/10.1038/s41598-024-52728-7

[8] Lu, Z., Morita, M., Yeager, T.S., Lyu, Y., Wang, S.Y., Wang, Z., *et al.* (2024) Validation of Artificial Intelligence (AI)-Assisted Flow Cytometry Analysis for Immunological Disorders. *Diagnostics*, **14**, Article 420. https://doi.org/10.3390/diagnostics14040420

[9] Li, J., Chong, T.W., Fong, K.Y., Han, B.L.J., Tan, S.Y., Mui, J.T.S., *et al.* (2025) Will Artificial Intelligence (AI) Replace Cytopathologists: A Scoping Review of Current Applications and Evidence of A.I. in Urine Cytology. *World Journal of Urology*, **43**, Article No. 200. https://doi.org/10.1007/s00345-025-05583-8

[10] Chen, X., Xu, H., Yu, S., Hu, W., Zhang, Z., Wang, X., *et al.* (2025) AI-Driven Transcriptome Prediction in Human Pathology: From Molecular Insights to Clinical Applications. *Biology*, **14**, Article 651. https://doi.org/10.3390/biology14060651

[11] Edelmers, E., Ņikuļins, A., Sprūdža, K.L., Stapulone, P., Pūce, N.S., Skrebele, E., *et al.* (2024) AI-Assisted Detection and Localization of Spinal Metastatic Lesions. *Diagnostics*, **14**, Article 2458. https://doi.org/10.3390/diagnostics14212458

[12] Zhang, H., Meng, Z., Ru, J., Meng, Y. and Wang, K. (2023) Application and Prospects

of AI-Based Radiomics in Ultrasound Diagnosis. *Visual Computing for Industry, Biomedicine, and Art*, **6**, Article No. 20. https://doi.org/10.1186/s42492-023-00147-2

[13] Jeon, K., Park, W.Y., Kahn, C.E., Nagy, P., You, S.C. and Yoon, S.H. (2024) Advancing Medical Imaging Research through Standardization. *Investigative Radiology*, **60**, 1-10. https://doi.org/10.1097/rli.0000000000001106

[14] Harari, Y.N. (2017) Reboot for the AI Revolution. *Nature*, **550**, 324-327. https://doi.org/10.1038/550324a

[15] Yao, S., Shen, P., Dai, T., Dai, F., Wang, Y., Zhang, W., *et al.* (2023) Human Understandable Thyroid Ultrasound Imaging AI Report System—A Bridge between AI and Clinicians. *iScience*, **26**, Article ID: 106530. https://doi.org/10.1016/j.isci.2023.106530

[16] Samuel, H., Norman, T., Vaknin, S. and Saban, M. (2024) The Physician-AI Relationship: Partnering for Precision Medicine via Clinical Decision Support. *European Journal of Public Health*, **34**, ckae144.1125. https://doi.org/10.1093/eurpub/ckae144.1125