



Artificial Intelligence in Medical Laboratory Technology: Current Applications and Future Perspectives

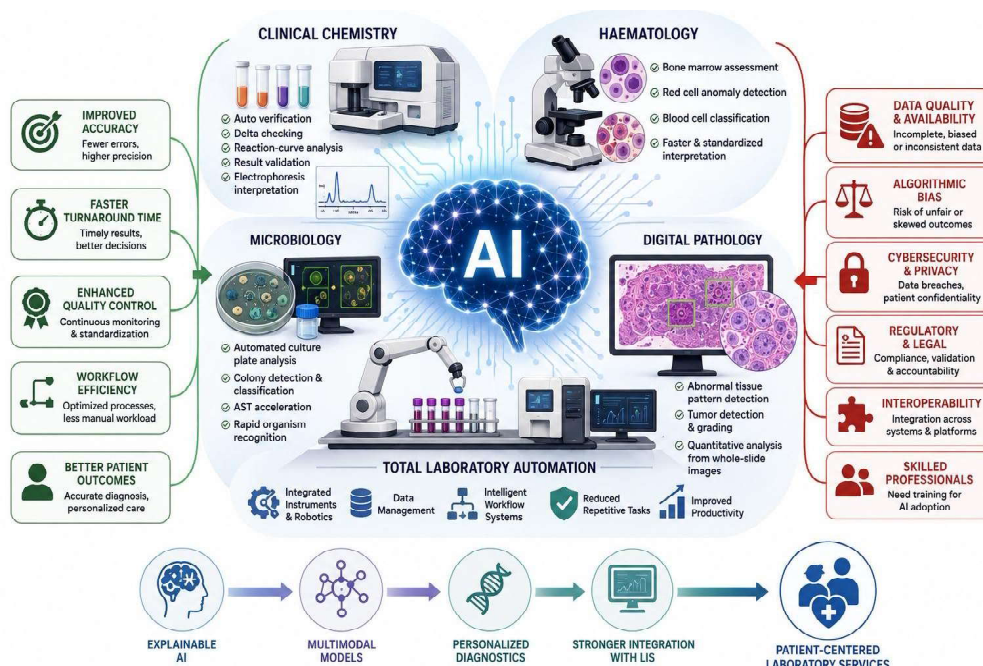
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ABSTRACT

Artificial intelligence is changing laboratory technology really fast. It is doing this by adding machine learning and other things to lab work. This review talks about how artificial intelligence's being used now what is good about it what problems there are and what might happen in the future. Artificial intelligence is being used in areas of laboratory medicine like clinical chemistry, haematology, microbiology, digital pathology and laboratory automation. In chemistry artificial intelligence helps with checking results and making sure they are correct. This means there are mistakes and the work gets done faster. In haematology artificial intelligence helps with looking at bone marrow and blood cells. In microbiology labs artificial intelligence helps with testing to see what medicines will work on infections. Artificial intelligence is also used in pathology to look at pictures of tissues. It can help find tumours and figure out what kind they are. Artificial intelligence is making laboratory work more efficient by connecting machines and computer systems. Some of these problems are data, biased algorithms and keeping patient information safe. The need, for experts who understand artificial intelligence. In the future artificial intelligence will get even better. This will make diagnosis more accurate and help patients more. Overall artificial intelligence has a lot of potential to change laboratory technology for the better. It can make diagnosis more exact and quicker.

Keywords: AI; Medical Lab Tech; Machine Learning; Clinical Chemistry; Haematology; Microbiology; Digital Path;



GRAPHICAL ABSTRACT

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1. INTRODUCTION:

Artificial intelligence (AI) is a recent concept that integrates more and more into all areas of human activity, including healthcare (Ahmad et al., 2021). AI can perform various intellectual functions that are characteristic of the human brain, such as learning, reasoning, perceiving, decision-making, or problem-solving. The appearance of ChatGPT in November 2022 attracted even more attention to AI, especially to generative artificial intelligence. Such models as Google Gemini, Microsoft, Copilot, DALL-E (Baxi et al., 2022). AI can change the way of testing, data analytics, decision-making, automate laboratory work, and individualize treatment. For laboratory medicine, the use of artificial intelligence can make tests safer, more convenient, and highly productive, help in making decisions, analysing massive amounts of data, increasing diagnostic accuracy, and predicting disease processes. Algorithms can be used to process patterns in laboratory and clinical data to perform various tasks in an automated (Baron & J. M., 2023) mode or in combination with humans. The majority of these algorithms are based on machine learning (ML), which enables computer systems to act without programming and learn from experience. There are three types of ML: supervised, unsupervised, and reinforcement learning (Bunch et al., 2023). To build and train such models, it is necessary to have reliable and high-quality data that will meet all the requirements and conditions. This is due to the fact that lab professionals have knowledge and skills in validating and verifying processes, quality control, quality assurance, documentation, performance evaluations, and data analysis (Cui et al., 2021). These three fundamental aspects of laboratory practice are critical to AI innovations to ensure their safe and effective use. Also include, issues related to clinical validation, transparency, liability, patient safety, data privacy, and accuracy across populations are crucial and deserve attention. Consequently, laboratory professionals (Durant et al., 2021) need to play a leading role in designing, validating, regulating, and using medical artificial intelligence for the sake of patients and public health. Particular attention should be paid to standardized data sets, clinical validation, quality assurance, monitoring, laboratory analytics, interoperability, and education. In general, artificial intelligence is a powerful tool that can have a tremendous impact on clinical laboratory medicine and Healthcare art (Esteva et al., 2021).

2. AI IN CLINICAL CHEMISTRY, HAEMATOLOGY, AND MICROBIOLOGY LABORATORIES:

Laboratory medicine has a main areas, like Clinical Chemistry, Haematology and Microbiology. Each of these areas uses its special Artificial Intelligence models. These Artificial Intelligence models are made for the tools and data used in each area of laboratory medicine (Heounjeong, 2022).

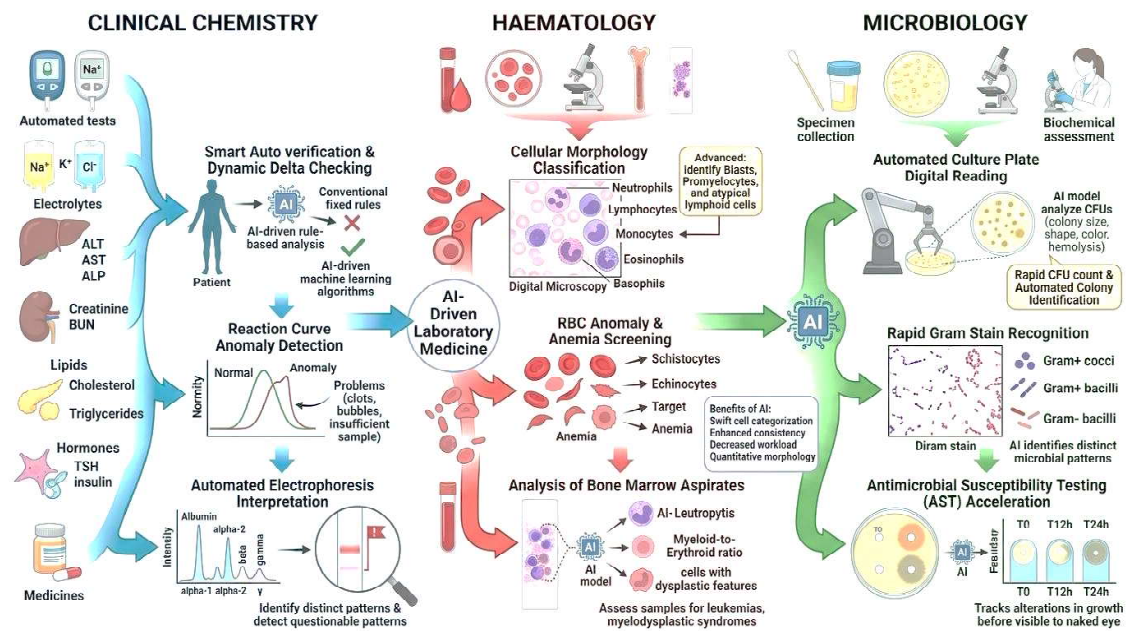


Fig. 1: Better diagnostic accuracy, automation, quality control and turnaround time are changing clinical chemistry, haematology and microbiology labs. It helps to interpret the biochemical results, identify abnormal blood cells, detect the microorganisms, interpret the culture and susceptibility patterns and support early detection of the diseases.

2.1. Clinical Chemistry Laboratories:

Clinical chemical laboratories perform a large numbers of automated test everyday. These test measures important substances in blood like glucose, electrolytes and various enzymes. They help the major organ especially liver, kidney are functioning. Labs test for lipids, hormones and medicines in the blood. There is much work to do and because results need to be fast and accurate, artificial intelligence and machine learning are being used more and more(Hou et al., 2024).

Smart Auto verification and Dynamic Delta Checking:

Conventional auto verification systems use fixed rules like reference ranges, thresholds, analytical indicators and set delta-check limits. These rules are helpful. May not fully take into account unique patient traits or complex combinations of test results(McGenity et al., 2024). AI-driven autoverification uses machine learning algorithms trained on laboratory data and long-term patient information to look at many factors at the same time. Possible contamination or dilution of the sample Contamination from IV fluids especially when electrolyte patterns are strange Mix-ups or errors in sample identification(Mitra et al., 2023).

Reaction Curve Anomaly Detection:

There are automated systems that do clinical chemistry and immunoassay tests. These systems make graphs that show what happens during the test. Usually people who check the quality of these tests only look at the number. They might miss something that's not quite right in the way the test is working. The system learns what a normal test looks like. This can help find problems like clots or particles in the sample air bubbles in the machine or if the machine did not get enough sample(Rabbani et al., 2022).

Automated Electrophoresis Interpretation:

Serum protein electrophoresis(SPEP) and immunofixation electrophoresis generate intricate graphical patterns that need skilled laboratory experts for analysis. Algorithms in machine learning can identify distinct patterns in electrophoretic fractions like albumin, alpha-1, alpha-2, beta, and gamma regions. They can also detect questionable patterns that might need additional scrutiny. AI can help in flagging possible monoclonal protein bands, uncommon gamma-region patterns, polyclonal gammopathy patterns, alterations indicative of notable protein abnormalities(Alrafiah & A.R., 2022).

2.2. Haematology Laboratories:

Haematology is about looking at blood cells and bone marrow cells. It is also about the shape of these cells. You need to be very good at this and look at the cells closely with a microscope. Nowadays machines can do a lot of the work. They can count the blood cells. Tell us what is in the blood. Sometimes the machine finds something that is not right. When this happens people who work in the lab need to look at the blood cells(Shmatko et al., 2022).

Cellular Morphology Classification:

Digital microscopy systems that use Artificial Intelligence can look at high resolution pictures taken by slide scanners. Artificial Intelligence can. Count individual cells on its own, which saves time that would be spent counting cells by hand(Viswanathan et al., 2022). Digital microscopy systems powered by Artificial Intelligence can identify kinds of leukocytes such as Neutrophils, Lymphocytes, Monocytes, Eosinophils and Basophils. Advanced Digital microscopy systems powered by Artificial Intelligence can even identify cells that are not normal such as Blasts, Promyelocytes and immature granulocytes Band neutrophils.(Janabi & S., 2022)

RBC Anomaly and Anemia Screening:

The shape of blood cells offers valuable insights into various forms of anemia and other blood-related conditions. To understand blood cells a skilled expert has to look at the size and shape of red blood cells how they are arranged and how much hemoglobin they have. Computer systems that use intelligence to look at images can quickly and fairly analyze a lot of red blood cells. These artificial intelligence systems can help identify blood cells that do not look normal such as Schistocytes.(Asif et al., 2023)

Analysis of Bone Marrow Aspirates:

Bone marrow analysis is an important test to find out if someone has leukemias, myelodysplastic syndromes or other blood diseases. Systems that use intelligence to look at pictures can help doctors assess bone marrow samples by finding and identifying the types of blood cells. It can also calculate the ratio of myeloid to erythroid cells, which is called the myeloid-to-erythroid ratio find cells look for problems with the cells that make platelets and point out things that might mean someone has myelodysplastic syndromes(Marletta et AL., 2023).

Benefits of AI in Haematology:

The application of AI in hematology offers benefits. Swift cell categorization is possible because large numbers of blood cells can be analyzed quickly. Enhanced consistency is achieved because Decreased

workload is possible because AI can do the step of grouping and counting cells. Quantitative morphology allows for counting of abnormal red blood cells and other cell types (Shelka et al., 2023).

2.3. Microbiology Laboratories :

Clinical microbiology has historically relied on manual specimen handling, cultivation methods, microscopic analysis, biochemical assessments, and visual evaluation of culture plates. The combination of artificial intelligence (AI), computer vision, digital imaging, and automated culture systems is revolutionizing microbiology by facilitating quicker image assessment, automated colony identification, and early forecasting of clinically significant outcomes (Sajithkumar et al., 2024).

Automated Culture Plate Digital Reading:

Conventional culture plates are usually looked at by hand to see how colonies develop what shape they are, what color they are if they show hemolysis and other traits. Microbiology system can count colony-forming units (CFUs) tell if there is bacterial growth or not follow how colonies grow during incubation check things like colony size, shape, color and hemolysis patterns tell the difference between important growth and background or contaminant growth in the right workflows (Hou et al., 2024).

Rapid Gram Stain Recognition:

Gram staining is a key preliminary method in clinical microbiology. It offers preliminary insights into the Gram reaction and morphology of microorganisms, assisting clinicians in choosing suitable initial antimicrobial treatments. Systems for image analysis based on AI can analyze digital images stained with Gram and identify distinct microbial patterns. AI can help in sorting organisms into categories like Gram- cocci Gram-negative cocci, Gram-positive bacilli Gram-negative bacilli or other types that can be recognized by their shape (Evans et al., 2024).

Antimicrobial Susceptibility Testing (AST) Acceleration:

Antimicrobial susceptibility testing (AST) is vital for estimating if a microorganism is exposed or resistant to particular antimicrobial agents. Traditional AST approaches frequently need adequate bacterial proliferation prior to assessing susceptibility. AI has the potential to enhance AST by examining digital images of bacterial growth across various time intervals. In techniques like disk diffusion, computer-vision systems can track alterations in growth around antimicrobial disks and detect minor variations before they are readily visible to the naked eye (Pantanowitz et al., 2024).

3. AI-ASSISTED DIGITAL PATHOLOGY AND LABORATORY AUTOMATION

Digital Pathology and Total Laboratory Automation or TLA are really steps forward in laboratory medicine today. They bring together good digital pictures, artificial intelligence, robots, machine learning and automated systems for laboratory information. These Digital Pathology and Total Laboratory Automation technologies make it so people do not have to work much they make the results more accurate they help the laboratory get more work done and they make it easier to make decisions about what is wrong, with someone (McGenity et al., 2024).

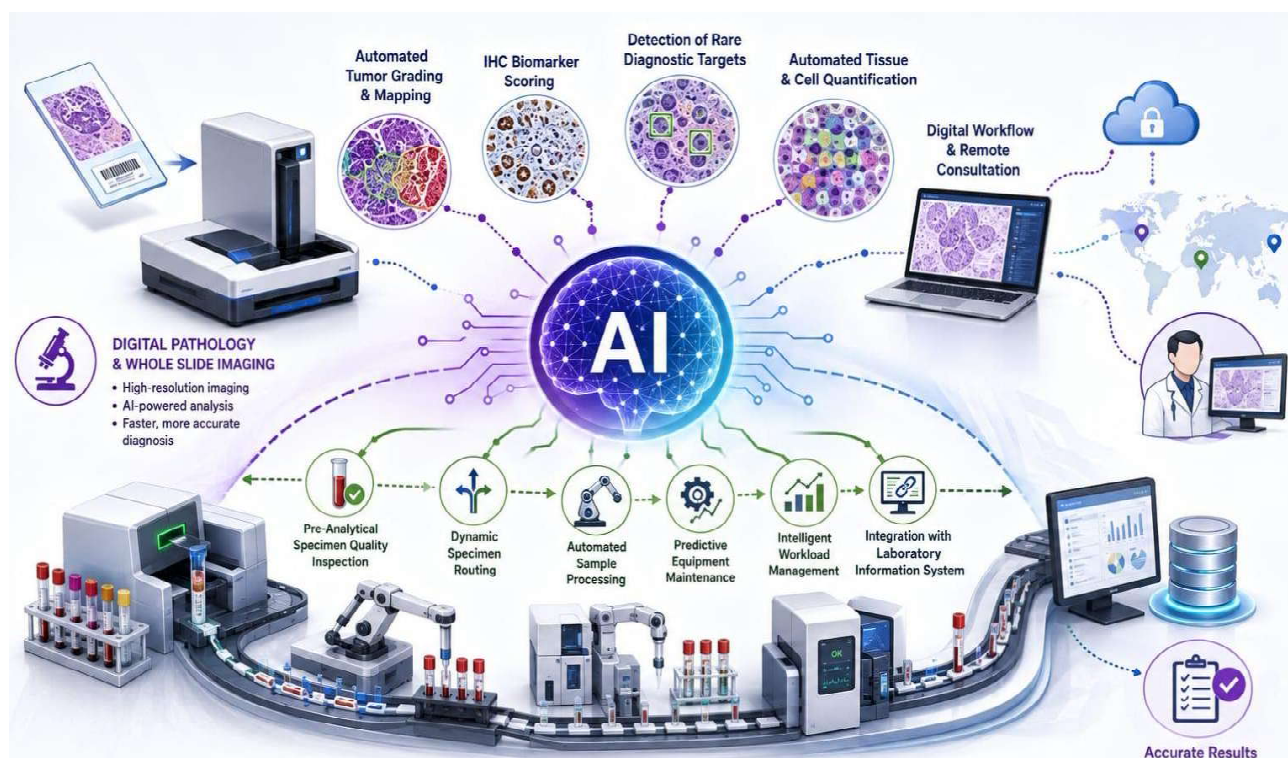


Fig. 2: AI analyses digital tissue and cell images to detect abnormal patterns and support diagnosis. It also automates sample processing, result validation, quality control, and laboratory workflows, improving accuracy and efficiency.

3.1. Digital Pathology and Whole Slide Imaging (WSI):

Digital pathology is about changing the way of looking at glass slides to digital pictures. We use machines to scan these slides and they become high-resolution digital images. These digital images, called Whole Slide Images are really big. Have a lot of details. We can look at Whole Slide Images on a computer. See the tissue samples really closely. We can use computers to look at Whole Slide Images and find things that're hard to see with our eyes(Jackson et al., 2025).

Automated Tumor Grading and Mapping:

AI-driven image-analysis technologies can draw exact lines around the tumor areas the edges of the tumors and the cells that do not look normal in tissue samples. These technologies can look at how much tumor is present, figure out how tightly the cells are packed, notice when the nucleus of a cell is not the right shape and help the people who study tissue called pathologists decide how severe the tumor is(McCaffery et al., 2025).

Immunohistochemical (IHC) Biomarker Scoring:

Immunohistochemistry is a method which helps doctors find biomarkers in the body. These biomarkers are important for figuring out what is wrong with someone and also for choosing the treatment(Rashidi et al., 2025). When doctors look at the results of Immunohistochemistry they usually just look at the colors. Try to guess how strong the colors are and how many cells are affected. We use Immunohistochemistry to look for things like HER2, Ki-67 ER, PR and PD-L1.(Brodsky et al., 2025)

Detection of Rare Diagnostic Targets:

When doctors look at tissue samples they might find some things that are only in a very small part of the sample. It can take a time to look for these things by hand. Deep learning algorithms can look at the tissue sample and find the parts that are a problem. These algorithms are used for things like finding micrometastases in lymph nodes, finding acid-fast bacilli in tuberculosis samples, finding *Helicobacter pylori* in gastric biopsies, finding rare malignant cells in tissue sections and looking for certain cellular or morphological abnormalities(Aggarwal et al., 2025).

Automated Tissue and Cell Quantification:

AI is capable of doing measurements that can be counted and are hard or take a lot of time when done by hand. It can count cells, nuclei, dividing cells and different parts of tissue while calculating numbers like how many cells are, in an area how big the nucleus is compared to the rest of the cell and how big the tissue is. This gives steady information, which can help with finding out what is wrong doing studies predicting what will happen and checking how well treatment works(Verma et al., 2025).

Digital Workflow and Remote Consultation:

Electronic storage of slides makes it possible to access them from many places. This makes it easier to do pathology consultations get second opinions do digital education and training have multidisciplinary discussions work on AI algorithm research and development and keep digital records for a long time(Tiwari et al., 2025).

3.2. Total Laboratory Automation (TLA) and Robotics:

Total Laboratory Automation is when you put together machines that can do things on their robots special tracks that things can move on computer programs and systems that help keep track of what is going on in the lab. This helps get specimens ready then it helps analyze them. Finally it helps manage what happens after that(Rashidi et al., 2025).

Pre-Analytical Specimen Quality Inspection:

The pre-analytical phase is where a lot of laboratory mistakes happen. Vision systems that use Artificial Intelligence can look at the specimen tubes before they are tested. Automated systems can check a things like, if the specimen tube and barcode are correct, if the tube and patient are properly identified, if the sample has the amount of volume and is filled to the right level, if there are any clots or other problems that can be seen, if the centrifugation was done correctly, if the sample is okay and, if there are any issues with hemolysis, icterus and lipemia which are referred to as HIL(Marchevsky et al., 2026).

Dynamic Specimen Routing:

In labs samples usually follow pretty standard steps. AI-driven TLA systems can change how samples are sent based on whats happening with the lab equipment now. For example the system can send samples to machines that are working avoid machines that are not working spread the work, between machines take priority for urgent samples send samples for more tests when needed and send samples again for testing if certain rules are met. This makes things faster(Bhavsar H., 2026).

Automated Sample Processing:

Robotic systems are capable of executing various repetitive laboratory duties with little human involvement. These might consist of – Sample sorting, Centrifugation, Decapping and recapping, Aliquoting, Sample transportation, Loading and unloading analyzers, Refrigerated sample storage, Retrieval of preserved specimens. Automation helps with tasks that are done over and over again. It makes those tasks easier and faster.(Fang & Chen., 2026)

Predictive Equipment Maintenance:

If something is not right with the equipment the equipment will send us a message. The computer can look at all this information. Detect patterns that might mean something may go wrong. This is really useful because it means we can fix the instrument before it breaks down fully. We call this maintenance(Rashidi et al., 2025).

Intelligent Workload Management:

AI is able to keep checking the number and type of samples coming into the lab and compare them with what the analyzers can handle. It can then improve the way tasks are assigned to the instruments. For example if one analyzer is too busy the samples can be sent automatically to another analyzer that's available. This helps in keeping a process when there are a lot of samples to handle(Rajkumar et al., 2022).

Integration with Laboratory Information Systems (LIS):

TLA works most efficiently when robotic systems, analysers, AI software, and the Laboratory Information System are interconnected. The integrated system can automatically: Receive specimen '! Identify and verify '! Inspect quality '! Centrifuge '! Sort '! Route '! Analyze '! Validate '! Report '! Store

This creates a constant digital workflow with minimal manual intervention(Acosta et al., 2022).

4. CLINICAL BENEFITS, QUALITY ASSURANCE, AND DIAGNOSTIC ACCURACY:

When we talk about patient care, clinical advantages and quality assurance and diagnostic precision all work together to make sure patients are treated safely. Clinical advantages and quality assurance and diagnostic precision are all important for care and all work together to help patients get the care possible (Lin et al., 2021).

Subsection	Key focus	Role of Artificial intelligence (AI)	Clinical and operational benefits	Reference
Turnaround Time (TAT) operational Throughput	Lab tests require processing. Lab tests require reporting.	Routine chemistry and haematology results are compared with pre-defined rules using AI-assisted auto-verification to identify abnormal, critical or inconsistent values for manual review. Linking laboratory devices, with Laboratory	AI reduces turnaround time (TAT) and enables more samples to be processed effectively in a given amount of time by automating common laboratory procedures. Laboratory workers can concentrate on compli-	(Yépez et al., 2022)

Table (Continued)

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Subsection	Key focus	Role of Artificial intelligence (AI)	Clinical and operational benefits	Reference
Quality Assurance and continuous Statistical QC	Detection of pre-analytical and analytical errors	Information Systems (LIS) makes sure that moving, checking and reporting results goes smoothly.. I have found that AI can watch laboratory samples and spot issues such as patient identification mismatches, wrong collection tubes, too little sample volume, damaged or unsuitable specimens and delays, in sample processing. By looking at sample information and laboratory workflow data AI can warn about errors before testing or reporting. This helps to lower -analytical errors raise sample quality and boost patient safety.	cated, unusual, or technically challenging samples when routine results are handled automatically. AI helps find sample identification errors, wrong containers, low sample volume, contamination and unsuitable specimens before they spoil test results. Constant monitoring of lab processes makes sample quality better. Improves quality-control habits while early detection of errors lessens the chance of wrong reporting and backs safer and more trustworthy patient care.	(Bunch et al., 2022)
Diagnostic Accuracy	Accurate identification and classification of diseases is essential.	I have seen how AI can analyse volumes of laboratory data and digital whole-slide images (WSI) to recognise complex patterns that may be difficult to identify manually. In pathology computer vision and deep learning algorithms can detect tissue architecture, cellular changes and disease associated features helping pathologists identify suspicious areas more efficiently..	AI assists pathologists, by highlighting areas identifying abnormal cellular and tissue patterns and providing quantitative image analysis. AI can help differentiate between diseased tissues and support the classification of various pathological conditions. When used alongside expert review AI improves the consistency, efficiency and accuracy of diagnosis while reducing the possibility of overlooking abnormalities.	(Turgut et al., 2023)

5. CHALLENGES, ETHICAL ISSUES, AND REGULATORY CONSIDERATIONS:

Although AI has a lot of things to offer using it widely means dealing with problems related to technology, morals and rules. AI has a lot of things to offer using it widely means dealing with problems related to technology, morals and rules(Krishnamoorthy et al., 2024).

5.1. Technical Challenges & Data Interoperability:

System Fragmentation is a problem. We need to get Laboratory Information Systems and Electronic Health Records and other software to work with Artificial Intelligence models. This means we have to follow rules like HL7 and FHIR and DICOM. Model Interpretability is like a box. This means Artificial Intelligence can be hard to understand. Healthcare professionals need to know what the Artificial Intelligence is thinking.(Zhang et al., 2025)

5.2. Ethical Concerns & Data Privacy:

To make intelligence that can diagnose problems we need to know about patients health. We have to make sure we follow the rules like HIPAA and GDPR to keep this information safe. We also need to make sure we remove any information that could be used to identify someone so we do not accidentally share their information. We need to say who is to blame whether it is the people who made the software the people, in charge of the lab or the doctors who are taking care of the patients Algorithmic Bias and Health Equity is a deal because we do not want these models to make mistakes that hurt people from certain groups(Varghese et al., 2024).

6. FUTURE PERSPECTIVES:

Ai and clinical LLMs will put all of results together in a simple summary that doctors can understand.

6.1. Advanced Laboratory Automation:

The future of intelligence in laboratory medicine looks like it will have many different parts working together. This will include things like looking at lots of test results and using artificial intelligence to help doctors write reports(Chen et al., 2026).

6.2. Multi-Omics Data Integration:

Future diagnostic systems will bring together lab tests like chemistry and blood counts with advanced technologies like Next-Generation Sequencing, which looks at DNA and other detailed studies like how genes work, how proteins behave and how chemicals in the body function. Artificial intelligence systems that work in ways will bring all this complicated data together with long-term health records to find early signs of diseases like cancer, brain diseases and problems, with how the body processes energy(Kelly et al., 2021).

6.3. Generative AI & Large Language Models in Reporting:

Generative AI and clinical LLMs will make it easier for doctors to understand laboratory results. AI is expected to improve the automation and efficiency of laboratories. In the future AI might help with finding samples organizing them handling them looking at them checking the outcomes and sending the information. Automation can reduce work done by hand lower errors and make the lab work better(Wiens et al., 2022).

6.4. Early and Predictive Diagnosis:

Artificial intelligence can help doctors figure out if someone is, at risk of getting a disease by looking at their past and current lab results and other health information. This helps doctors find out if someone is getting sick so they can do more tests or help the patient sooner (Moor et al., 2023).

6.5. Reduction in Turnaround Time:

Workflows that use AI can help in deciding which samples need attention first making the work easier to manage and making it quicker to look at the results. This can make the time it takes to get results shorter and let doctors and nurses get lab information more quickly especially when patients are in emergency or critical condition (Neogi et al., 2022).

6.6. Next Generation Point-of-Care Testing (POCT):

Smartphones can be used with devices that're very small to test people's health. These small devices are designed to check aspects of a person's health. These devices are connected to smartphones. Use special computer programs to get very accurate results. They can be used in hospitals, community health centers and even in places that're very far away (Bryksin & Salehi, 2025).

7. CONCLUSION:

Artificial Intelligence is changing Medical Laboratory Technology into an automated data-focused, efficient and predictive field. AI-based systems can help in the detection of abnormalities, reduce manual mistakes, improve turnaround time and support better clinical decisions by making pre-analytical processes more effective, taking morphological analysis in hematology and digital pathology to a new level, improving microbiological workflows and increasing laboratory automation. The use of Artificial Intelligence and Medical Laboratory Technology is a development, for laboratory services. It means we can get results that're smarter and faster and more accurate. We can also spend time on the patients. If lab professionals and clinicians and researchers and tech developers all work together, Artificial Intelligence can make a difference in the future of laboratory medicine. Artificial Intelligence and Medical Laboratory Technology can really help us improve laboratory services (Fang et al., 2023).

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