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The Application of Artificial Intelligence in Medical Laboratories for Ensuring Accurate Sample Collection and Processing

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Abstract
Human error is standard in every human's profession, and it is also the case for healthcare. In medical laboratories, human error can occur in several steps. In laboratory medicine, the pre-analytical phase is crucial to obtain reliable test results. However, it is prone to a lot of pitfalls, mistakes, and errors leading to increased testing time but also to misdiagnosis. Some process errors leading to decreased test result reliability can be avoided, even more easily using specific automatic AI methods.

Keywords: AI, Medical Laboratories, Healthcare, Human error, Misdiagnosis, Quality Control, Error Detection, Sample Processing, Sample Collection

1. Introduction to AI in Medical Laboratories

In the analysis of Point of Care (POC) customer feedback data, getting (2018) identified two themes of problematic testing and self-misreporting, suggesting that processes such as Liebman and Conrad's R&D phase are important but may not suffice to ensure accurate sample collection in all cases. This is a problem because the Centre for Disease Control (CDC) attributes the preanalytical phase to be responsible for 46–68% of all laboratory errors, with 35% of these due to sample collection errors, potentially causing consequences such as misdiagnosis, incorrect drug administration and patient discomfort. This is particularly concerning given that this phase is entirely or partially under the control of the customer. Moreover, Church (2012) recently found many customers are not following recommended procedures such as using turnstiles or sinks directly before fingerpricking. Currently, it is unclear to what extent these findings generalise to standard practices of in-site sample collection. Hence, there is a possibility that the problems Make will identify in the collection of the dried capillary blood may also be problematic when collecting a single capillary of fresh blood. Thus, there is a need for further research, and as the world moves increasingly online, it is important to extend this research into the health science context, particularly in relation to at-home collection of capillary blood [1].

The use of artificial intelligence (AI) in medical laboratories has been found to enhance sample quality and throughput. In an era in which healthcare costs are under constant scrutiny, laboratory professionals often find themselves in need of doing more with less. Laboratory professionals continue to seek innovative solutions, often in the form of new and advanced technologies, to solve these problems [2]. AI has been leveraged to perform or assist in several functions in the medical laboratory. In the preanalytical phase, AI has the potential to eliminate some of the common causes of error. On the analytical side, AI has been used to analyze and interpret laboratory data. Some of the barriers to the routine use and integration of AI are consistent with many other clinical applications and need to be addressed. As embedded AI continues to rise in medical laboratories, it is essential that stakeholders are all familiar with the benefits and consequences of these products to promote the implementation of potently effective technologies that will help to underpin the future of clinical laboratories [3].

1.1. Definition and Scope of AI

The AI in medicine was mainly used in the following three areas: in the development of medical devices such as implantable cardioverter-defibrillators; in the field of diagnostic imaging, in 2021 deep learning (DL) algorithms have received regulatory approval or soon to automate image interpretation and in situ diagnosis of medical images; and, for research purposes to explore biologic data. However, the COVID-19 epidemic and subsequent worldwide pandemic accelerated the interest in using AI as a helpful tool in the healthcare system in general and specifically in clinical laboratories. It has been quickly realized that this technology can be used to improve healthcare quality, support medical personnel in their work and medical decision-making process.

In artificial intelligence (AI), software-based algorithms are used to build, validate, and optimize solutions in various technological domains [4]. AI can support improvements in diagnosis and in treatment planning for individuals, and in predicting epidemics, diseases prognosis, drug performance and in reducing healthcare related costs. Finally, it is used in biotechnology and in personalized medicine, and represents an essential part of building and delivering medical knowledge [5]. Moreover, this technology is the basis for many contemporary medical devices which use AI. AI is rapidly changing healthcare industry and medical practice. It is opening new possibilities and introducing new challenges. It might be applied in many spheres of medicine and could revolutionize the way in which healthcare is delivered to patients, especially in relation to vast number of information generated in medicine, the artificial intelligence is an essential tool to manage and analyses this variety of data. Therefore, AI contributes to the development of personalized medicine and supports physicians' therapeutic decisions [1].

1.2. Importance of AI in Healthcare

The Internet of Medical Things has become one of the most popular technologies in current tough days in addition to Artificial Intelligence, because IoT represents an essential channel for encoder/decoder a big variety of health data, in collecting data from the laboratory, medical imaging clinics, primary care clinics, and many others. Each day, health institutions are obliged to store a big volume of clinical data. There are so many different sets of clinical data generated each day, throughout the year. It is impossible to examine this big data to extract and search for valuable and relevant clinical information in an acceptable time range without even artificial intelligence. "Remote testing and monitoring" interaction also made it hard with AI technologies, either the built Middleware services or the classic AI tools being offered to the medical and health community come to an exist to overcome the afore-mentioned obstacle.

The use of artificial intelligence (AI) technologies in healthcare is driven by the need to improve processes, including diagnostic procedures [6]. Routine laboratory tests are widely used because they provide extensive information about health status and the functioning of different body systems. A growing number of biomedical tests have been made available that are used in different medical specialties every year generating a huge number of results. These results are spread over different platforms/systems and need to be sorted, analyzed, and interpreted. Data from clinical laboratory has the highest impact on medical decision making. It allows many aspects of patient care to be monitored, provides indirect indicators to diagnose latent illnesses, and is used to prescribe treatments, but only a very limited number of rules are known and implemented for them. The use of AI in different medical activities and fields has been debated, and the use of clinical laboratory data is no exception. AI technologies provide new types of information on existing tests, raise new issues about how to handle patients, and anticipate health states while direct application and validation of existing tests has been postponed. Moreover, biases and disparities in AI decision making among different races or between sexes exist but have been identified in laboratory tests.

2. Challenges in Sample Collection and Processing

Challenges related to test datasets are addressed in the recommendations by the ESP Working Group on Scientific Affairs on these data. Our document is primarily targeting AI engineers and developers to help them on how to compile performance benchmarks more accurately and homogeneously for the most prolific digital pathology application areas [7]. In this document, we present the outcomes of working group sessions that propose general considerations for the creation of test datasets used to evaluate AI solutions for the assay of pathology algorithms and identify various challenges and pitfalls throughout the process. The guidelines are highly relevant for all parties involved in the development of diagnostic AI algorithms, and, if followed, should ensure more homogeneity and consequently a higher comparability of the considered studies. Importantly, a joint effort from all stakeholders is needed, including pathology procuring organizations, academic and industry partners, and clear regulations on how to access and distribute the data. Fundamentally, the standardization of digital pathology test datasets should be a precursor to methodologically sound AI-to-gold standard performance evaluation and can thus substantially foster the translational traffic of diagnostics in field [8].

The preanalytical phase of laboratory medicine is highly operator-dependent and can be responsible for up to 70% of errors in laboratory testing. Artificial intelligence (AI) solutions facilitate optimization at various stages of the laboratory process by providing increased accuracy, precision, and speed in evaluating histological findings, extracting digital biomarkers, and performing decision support accessibility [9]. This paper consists of two main parts: the first is a review of the literature on the current situation of AI in medical laboratories, and the second is a description of our ongoing development and implementation of an AI system for preanalytical laboratory process optimization. Reliable performance evaluation of AI algorithms is a prerequisite for successful translation of digital pathology and other laboratory AI-based solutions. A metrically sophisticated dataset of n ~ 500 digital whole-slides comprising clinical scenarios and their labels are to serve as new standard reference data for pathology AI validation, named the Prostate AI Challenge benchmark.

2.1. Variability in Sample Collection Techniques

The improper sample collection process may lead to medical errors [10]. Such errors later have severe outcomes causing financial costs 6. For example, inaccurate sample identification and labeling can lead

to sample mix-ups, and an association of incorrect patient information with samples of different patients for different investigations can lead to wrong results being reported [9]. The error in the sample collection process was reported in 1% of the National Health Services complaints and resolved between 34-50%, of which some resulted in lawsuits. Moreover, 55% of sample errors originated from the venous blood collection point; hence, training needs to be focused on phlebotomists. A survey report indicates that in 40.50% of cases, the medical staff made errors, 26.50% due to technological cognitive overload, 22.50% due to lack of knowledge, 5.00% due to mixed patient, and 5.50% due to negligence. The important impact on the errors was early detection, and pre- and post-analytical errors accounted for 71.20% of the total errors.

2.2. Human Error in Processing Samples

In a review from Carraro and Plebani, some of the most described pre-analytical errors, studies or descriptions refer to inappropriate sample volumes, led by healthcare workers due to inadequate standard operating procedures (n = 8). Also, several authors have demonstrated that the most common pre-analytical error is related to inadequate patient identification (n = 16). Besides wrong patient identification errors (n = 11), sample labeling was frequently reported in the review (n = 8). Transportation errors as a U-shaped compound cooling box during the delivery of samples or import time beyond 60 min after sample collection were also other factors of potential misdiagnosis by inadequate sample transport conditions. Prentice and Davies have confirmed these findings by reporting an incidence of causes for false and inaccurate laboratory results. The relationship between pre-analytical errors and the potential to correct them has been lacking in every study. Which is our methodological contribution to evidence that artificial intelligence could potentially help to reduce the effect of these errors by pressing the “pause button” at the pick-up event and subsequently goes through distinctive corrections by raising alerts to suggest solution possibilities or by delegating decision operations.

Human errors can be classified by hospitals as preventable and non-preventable, and it is a matter of adequate control and prevention. About one-fifth of all medical claims are due to an inaccurate or missed diagnosis, all of which is relevant in the developed AI system. Several authors have shown that these false or inaccurate results are related to substandard practice in the pre-analytical phase in about 46 to 68 percent. Because of human error, an increase in escalating healthcare costs occurs because of a lack of efficiency in processes, potential misdiagnosis, negative patient experiences, and even worse patient outcomes.

3. Role of AI in Enhancing Sample Collection

In conclusion, it has been briefly discussed the importance of the pre-analytical phase of laboratory analyses and the growing application of AI tools for enhancing patient safety in the era of precision medicine [12]. Most of the recent growth seems to be at first sight in the relatively chaotic risk and hazard management family – which is not surprising since it is arguably the more rewarding professionally to be involved in developing new highlights on the virtual world map of this captivating subfield. The diversity of the list also suggests that, as discussed in The Virtual Physiology Lab, different groups seem to struggle to agree on many shared objectives for risk in in vitro diagnostics, although one global theme that did or did not come up was the public health impact of low-impact technology. The investments becoming evident indicate that the informational as well as economic outputs from IVD AI risk and quality assurance lab are about to “spin off” in a multitude of non-

laboratory healthcare sectors beyond the hospital community. On the other hand, there are some proposals across which a few non-mandatory agreed risk and quality assurance red threads are drawn. The intersections between the results of the mapping exercise and the regulatory, metrological, and procedural opportunities are used as the basis for some short-term and long-term policy and general management proposals for defining and addressing IVD AI risk swamps as (national to transnational) virtual environments.

There are many sides to the application of AI in healthcare systems, and one of the major factors is its potential contribution in dealing with the errors in the first phase of laboratory analyses. Pre-analytical phase errors matter because they can have downstream implications with regards to the validity of the final measurements made for the patient, which can risk misunderstanding the context of diagnosis, prognosis, therapy selection, response to therapy and toxicity [10]. Active checking of patient identification at the time of sample collection is a bit of a common sight, whereby a staff member will confirm the patient's date of birth and name match a printed label on the request form and that the request form matches to a printed wristband on the patient. Increasing patient numbers and requirements for more evidence-based healthcare mean there is a greater reliance on some aspects of specimen collection being conducted by the patient. The ability to identify veins from the surface, and use them for positioning, and potentially for monitoring the success of blood collection, is the basis of one vein identification system that has been depicted in the literature [3]. One group of researchers has developed Sense•Aid, a smartphone application that helps surpass the memories of phlebotomists and patients, and autocup like that of a vending machine. The app greatly increased patient compliance in children when they estimated how long a step of the procedure had taken, and it dramatically increased compliance compared to the needs of reddish web all the department's staff and patients. Taken together, these findings show that AI has the potential to reduce sampling-related errors, and it could considerably assist staff in a supportive role.

3.1. Automated Sample Collection Devices

In the medical laboratory, the pre-analytical phase is the most vulnerable phase; it is particularly delicate and requires careful attention to avoid pre-analytical errors that may negatively influence the accuracy of the exams [13]. Among pre-analytical operators, laboratory operators and phlebotomists working at the collection centers represent the most important healthcare professionals involved in the process of drawing suitable specimens. As a matter of fact, blood collection is an area particularly critical to guarantee the correctness and reliability of laboratory test results, ensuring that the correct sample is drawn from the consent holder and that this sample is correctly and safely handled. In this context, it is very important to introduce practical measures to simplify the analytical processes and systems that guarantee sample closure, collection, identification, and traceability [6]. Automated sample collection devices are integral to the inertial automation of pre-analytical processes. These tools are easy to use, even by junior health workers, and efficiently collect highly accurate biological test samples by processing advanced algorithms that offer real-time sampling data. Automated sample collection devices usually offer exceptional safety and reduce the risk of stress and anxiety in users as well reduce the risk of unsatisfactory sample collection. Therefore, the application of AI is useful in processing clinical data and for obtaining faster and more reliable results. This application typically reduces the possibility of replication errors in case the sample was misidentified. It also improves the acquisition and the traceability of the required data and guarantees the utmost privacy and safety for test results [12]. When using an automated biometric fingerprint control system, for instance, it is difficult for an identification

error to occur, and it guarantees that the correct phonetic and printed data are matched flawlessly. This type of approach also offers the ability to recognize people who present with phonetic variants, thanks to the logic algorithms, maybe unconsciously misspelled, as it were to the automated audit trail.

3.2. Real-time Monitoring Systems

There are currently a few laboratory IT systems, which are aiming to use data of test requests and processed results to become a doctor or pick up abnormal clinical trend over even specific user for next action buy his capability. These are integrated single test selection and result analysis and PickAB tets and use data system by Lifecode LTD. Prevention of any potential electrical robotic medical professional by identifying proper laboratory information systems comprehensively until 2025 are indicated. The possible problems in a hypothetical model will be categorized, introduced, and examined in a corresponding hierarchical and pet shop. Based on the collection acceptance, possible solutions will be provided to find a robotic professional every time more than medical doctor for patients. All potential ways of intervention include a validation board must be discovered the best way to be involved in human medical laboratory performing a good effective result.

Real-time monitoring systems allow users to monitor and observe real-time situations, supporting the on-time extraction of results or alarms to ensure the safety and validity of any biological samples under test [1, 14, 21]. Modern real-time monitoring systems are harnessed in diverse medical fields to ensure safety and robustness of medical treatments comprising medicinal monitoring, intraoperative monitoring, telecardiology, telemedicine, robot-assisted surgery, smart surgical equipment, 3D robotic printing for drug and body organ copy, pharmacy automation, personality identification monitoring, virtual reality, and most of the medical device (implantable and wearable). AI-based smart-real-time monitoring will optimize and assure the on-time extraction of clinical clues/alarms to ensure the safety of any biological sample. Additionally, the privacy of users is ensured yet providing the best customization-friendly smart medicine for the diversified world citizens. Real-Time Jeans (RTjs) will be explained in safe real-time jeen technology, safe learning from real-life situation services, Mastermind medicine model, Big health care, MedWear, and a related sample of smart hospital in which will be presented the new patient senior intelligent interactive humanoid service, two realistic novel projects, the auto personalized smart-surgical department, and the smart autocentric wear of embodied intelligent carer, and the frequent used operation under smart robotic surgery, or smart clinical alarm customization, and New Medical Real Time Test Tools (NMR-TTS). The new safe jeencity in healthcare will represent new reactive multiway roads for real and sensible real time treatment at different level and a new safe C.A.R.E. model is introduced. A related model of medical real-time personalized safety services.

4. Role of AI in Improving Sample Processing

In this era, the introduction of fully equipped robotic workstations in pathology laboratories offers an unparalleled opportunity to streamline routine tasks and to drastically reduce human errors. AI solutions, either inbuilt in the robotic system or integrated after the staining, scanning, and case management steps, can provide both surveillance of hands-off efficiency for process improvement, as well as boost tissue and cell-based sorting and enumeration [15]. This development spares the humans from tedious chores, can provide completely new analysis, and may also lead the way to a concept of limited super vision/remote quality control advice [16].

Successful navigation of the complex nature of artificial intelligence (AI) in pathology lies in understan-

ding how AI tools integrate symbiotically with laboratory workflows. Yet, this understanding is not always transparent or discreet. AI solutions frequently attempt to integrate into the backend of the hospital information system with potential to create novel patterns in sampling strategies and laboratory results [3]. Knowing how to solve typical integration challenges and building POC connectors for quality assurance measures will improve the pipeline in digital pathology.

4.1. Automated Data Entry and Labeling

The most technologically advanced solutions for printing labels on the receptacles of material use ink jet and thermal printing technologies. These systems register barcode stickers and generate a dedicated print in a fraction of a second by digital technology, without the use of additional cartridge maintenance. Barcodes are read through machine vision cameras or linear optical scanners. These are the only systems that can handle the complete decoding of DPM (Direct Part Marking) codes on the plastic surface of the receptacle, which is becoming the industry standard of materials for tracking process.

Once data entry is automated, the entire process of patient material analysis is safer [10]. AI algorithms are developed to translate handwriting into computer graphics, and optical character recognition is responsible for transferring this data to electronic registration systems. The most accurate solutions use computer vision algorithms, which automatically locate individual barcodes during inspections. This results in the highest possible precision of a successful registration process in comparison to scanning stationary barcode systems. The use of AI in laboratory practice ensures the permanent tracking of samples and the immediate analysis of tracking data so that the courier can quickly return to the lost sample. The term confirmed by the fact that AI materials were lost only by one out of 2000 laboratories on departure.

4.2. Quality Control and Error Detection

A clear example of preserving laboratory test quality could be those tests which require the samples to be drawn with the right colored tubes. Our consolidated experience posits that labs end up needlessly re-collecting several vials that are significantly above the industry's generally acceptable threshold for poor sample collection. AI for quality control (AIQC) can process each individual signed disposal authorization, and automatically verify whether it was collected correctly, flagging those cases that failed color compliance. It can also be programmed to check both the type of vial and the number of samples collected for other tests (hormones, e.g. TSH/FT4) in blood or urine (microalbuminuria). If additional tests were prescribed, the system verifies the appropriateness of the surplus amount collected, thus predicting potential delays in diagnosis/treatment. In cases of improper sample collection (e.g. missing the serum separator gel), request printing can be suspended and a few unsuccessful attempts to resolve the impasse can be carried out before the request is blocked and a withdrawal request notification is promptly sent to the responsible doctor. The system also performs monthly monitoring of staff adherence to the good practices of sample drawing. As indicated by the IFCC, the harmonization of tests and methodologies, standardization of how the samples are collected, stored, and transported, are essential ways to support laboratories in the safe performance of their activities in an environment characterized by increasingly selective demand and high safety standards to follow.

Opportunities for artificial intelligence in medical laboratories extend to the pre-analytical phase, where routine but manual, error-prone activities are common. According to the International Federation of Clinical Chemists and Laboratory Medicine (IFCC), the pre-analytical phase refers to events and operative factors which impact the laboratory test results prior to release, and it ranges from test prescription to sample receipt by the lab, after both collection and transport have occurred [10].

Avoiding errors is essential to ensure the accuracy of the medical tests and reduce the need for upsetting repeats which, for the patient, could translate to additional costs and potentially dangerous delays in diagnosis and treatment. Most of these tasks can be improved through the application of AI. This can take several forms, for example improving the test prescription and the way the results are presented to the requesting physician (Clinical Decision Support Systems); a greater and more consistent control on how the collection, the preparation and the packaging of the samples should be put into effect; a better assessment of sample quality before the tests are started; a reorganization of tasks and duties within the laboratories in order to reduce errors in transport to the locations designated for the analysis.

5. Integration of AI with Laboratory Information Systems

The integration of AI technologies in modern LIS is expected to improve the performance and reliability of the laboratory in the long term. Cybernet gets the most information from LIS: orders, results, and control plans [17]. It supports the laboratory by means of intelligent algorithms, and it is a good starting point to broaden the spectrum of LIS functionalities with intelligent solutions. SMART, which can contextualize the information coming in from the laboratory information system and promote more intelligent behavior, should be regarded as a more advanced integration system. It can be thought of as a simple PID controller, which operates as a closed-loop system [13]. Laboratory test path can be regarded as an open loop system then the integration of cybernet and smart opens the doors to a step forward to the AI-based generalization of the control problem. It suggests that the combination of AI tools such as Cybernet and SMART, would allow an efficient reproduction of the intrinsic dynamics of the analyzers' behavior and help the laboratory to respond to the external perturbations. It confirms that this approach could be seen as a valid starting point for new intelligent enhancement of the analytic performances of the laboratory. SMART also analyses the virtual master (i.e. the schedule of the analyzers in a test path) to allow decisions on the feedback of results on samples [1]. It features an interpreter who observes the Pc performance and, by leveraging the analytical technique profile (clean responsive plateaus, cycle time, carry-over), selects the best response, returns, or reverses it, where necessary.

6. Ethical and Regulatory Considerations in AI Implementation

The need to employ good AI Non-Discrimination Acts/Acts of Fairness in the development of the original data of a product, and identify the lacunae of this data, in addition to the AEDIT-deviation and the difference with the result of the original product is one of the areas where ethicists expect to improve the practices of pharmadiagnostics industry. It is particularly concerning when it is observed that the biopharmaceutical uses a newer tests probably not entirely following what the product was originally labeled for, as also the antibiotic prescription patterns of clinicians are inclined towards the new drugs/ newer regimen where the drugs showed clin-ically marginal benefits in the clinical trials or—this occurs in the circumstance where biopharmaceuticals are not adhering to what was agreed as per the conditional approval path through which the said immune diagnostic got approval [18]. This underpinning imagination unearths excavates the dire necessity for ethical oversight thus necessitating the implementation of acts to stop the next morally outrageous happening in the healthcare domain.

Developing artificial intelligence (AI), particularly its commercial application across myriad industries, catches the attention of ethicists, regulators, and the public. Some of this attention is also focused on the application of AI in development of innovative products in the medical industry, most notably—autonomously operated healthcare devices 19. Unlike the traditional medical diagnostic devices, such

autonomously operated devices, powered with AI, can draw conclusions from internal and external data independently of operators who may run these, or readouts, to ensure patient care. These conclusions are beyond reproach of current norms associated with control or audit of functioning of a medical device and, therefore, are of concern also for regulators [20]. Esteemed medical diagnostic corporations work in accordance with the SCRUM development methodology, based on which products are developed rapidly (over weeks' long sprints, rather than longer than year long traditional FDA tier1 pathway) and released to the market based on the speed at which product development progresses, not necessarily the speed it matures through validation steps. This article is inclined to discuss the medical device ethical and regulatory aspects and not so much about re-engineering of fundamental immune diagnostics, the documentation related to clinical utility.

7. Case Studies and Success Stories

Integrated medical informatics systems will become increasingly vital for resource use, infection control, and personalized medicine. Some examples of AI utilization methods are also presented, identifying genomic mutations, formulating new targeted drugs, predicting responses to preexisting cancer drugs, and sharing reports on the study of mutations in human gene sequences. Integrated information networks and data mining techniques are now expected to contribute to health management. In medical surgery, the use of a 3D printer is an important innovative technique, but this 3D auxiliary treatment is supplemented by various techniques using robots, digital sign processing, and ranking requests of the Treasury Department. It is not widely practiced for medically essential purposes. In this section, the medical receipt of digital information is important for ensuring that the treatment by the microorganism diagnosis is freely correct, and the laboratory diagnosis is accurate.

This section reviews the application of AI in medical laboratories [5, 6]. AI can be used in human doctors, to facilitate decision-making, and to help doctors make decisions. AI tools can help predict which patients will be readmitted to the hospital, more effectively treat sepsis, and interpret laboratory results, such as microbiological samples. Laboratories receive a vast number of requisitions each day, and microorganisms are responsible for most healthcare-acquired infections. The need to identify the causative agent at an early stage and choose the most appropriate antimicrobial treatment emphasizes the need for a more effective laboratory tracking system for requests, samples, results, and clinical information.

8. Future Trends and Innovations in AI for Medical Laboratories

In all laboratories, AI will likely support pathologists with complex procedures in the future 5. Already today, systems are available that can suggest established diagnostic results based on image data. With increasing digitalization, these are being developed further to freely address these results. One major challenge in these systems is that the so-called "black box detection" lies: It is often difficult to understand in detail which image parameters and patterns are being analyzed by the AI. In the future, smart solutions will prove themselves here, e.g. that teach a neural network step by step to recognize liver metastases and then allow it to identify them safely.

In the foreseeable future, further AI developments are expected to be integrated into medical laboratories to provide expert analysis of increasingly complex information, optimally connected to other healthcare IT applications [21, 22]. AI is likely to provide definitive solutions in medicine to provide reliable analysis and predictions. In clinical settings all over the world, AI is increasingly used to provide second

opinions about diagnosis and to guide treatment responses.

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