



Review about Artificial Intelligence in Hematopathology; Current Uses and Future Opportunities

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Abstract

Hematopathology deals with the increasing workload and more complex cases that still relies on the microscope examination which takes a lot of time and can vary between observers. This review aims to explore Artificial Intelligence (AI) uses in hematopathology with its current applications, benefits, challenges and future opportunities. Artificial Intelligence (AI) tools—especially Deep Learning (DL) and Convolutional Neural Networks (CNNs)—show strong results, in automatically reading peripheral blood smears and bone marrow aspirates. Beyond morphological classification the review points out AI use in reading flow cytometry data and in predicting blood cancers such as Acute Myeloid Leukemia (AML) and Myelodysplastic Syndromes (MDS). The future of AI in hematopathology depends on combining data types. In that approach AI algorithms merge data, with immunophenotypic data, cytogenetic data and molecular profiles. AI algorithms then give risk grouping and treatment recommendations. However, there are still barriers to using AI in clinics. The black box nature of deep learning models is one barrier. The lack of diverse annotated data sets for training and need, for regulatory rules are another barriers. the review concludes that AI will become a decision support tool and will move the work from microscopy to digital, data driven computational pathology which will improve precision and efficiency.

Keywords Hematopathology; Artificial Intelligence; Deep Learning; Digital Pathology

1. Introduction

Artificial Intelligence (AI) is becoming a game-changer in many areas of medicine, including hematopathology which employs a number of different tests to look at blood cells and bone marrow, such as cytology, histopathology, and molecular testing. Because accurate diagnosis allows for personalized treatment plans for blood cancers, hematopathology is very important for making treatment choices. Also, because of advances in technology, particularly in AI, hematopathology is using more and more computer-based methods to make diagnoses faster and more accurate¹. The use of AI technology makes it easier to look at complicated data, for instance, AI may assist automate the study of blood cell morphology, which speeds up the process and cuts down on mistakes made by people. These changes highlight how hematopathology is evolving and how both old and new approaches may help improve clinical outcomes. Healthcare professionals may now examine vast amounts of biological data, such as cytogenetics and flow cytometry findings, due to the advancement of machine learning (ML) algorithms, which provide essential insights into hematological malignancies². Anand et al. asserts that the use of large datasets, such as Quilt-1M, which includes a diverse array of image-text examples, facilitates comprehensive model training, enabling AI systems to exceed traditional diagnostic methods in the categorization of intricate illnesses. Furthermore, recent advancements indicate that convolutional neural networks (CNNs) may precisely detect recurring chromosomal abnormalities, laying the groundwork for automated diagnosis⁴.

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This shows that AI can both help and change the way doctors make diagnoses, which will eventually lead to improved patient outcomes via quick and precise medical decisions. As AI technology continues to progress, its potential for future breakthroughs in hematopathology becomes more exciting and multidimensional, opening the door for enhanced clinical outcomes and healthcare delivery.

2. Current Applications of AI in Hematopathology

AI is changing how hematopathology works, AI algorithms, especially for looking at images, help measure blood-related details more accurately than doing it by hand. This usually means fewer mistakes and better guesses about how diseases might progress^{5,6}. Also, AI can sift through tons of data quickly, spotting complicated patterns in blood issues, which makes things run smoother in clinics. Another part is using AI for remote diagnoses, or telepathology, spreading expert knowledge to more places. All these improvements are pushing hematopathology towards being more effective and based on solid evidence⁷⁻⁹.

2.1. Application of AI in the diagnosis of haematological problems

2.1.1. Morphologic identification of haematological disorders

Because of the complexity of haematological illnesses, prompt diagnosis is essential for appropriate therapy. One frequent and successful clinical approach for diagnosing haematological disorders is cytomorphometric analysis of bone marrow smears. The first step in manual smear analysis is for a haematologist to identify an appropriate cell, and then to perform a differential cell count on hundreds of cells in order to classify the cells into different subgroups. Recent years have seen an improvement in morphological diagnosis thanks to the use of AI, ML, and digital morphological pathology analysis. Automated morphological recognition and classification of bone marrow samples is a strong suit of CNNs, which facilitates diagnosis of this process. The CatBoost and XGBoost algorithms are commonly employed by CNNs for this task. CNN has been utilised for the automated processing of bone marrow smears in the diagnosis of several haematological disorders, such as acute myeloid leukemia (AML), Myelodysplastic syndrome (MDS), and aplastic anemia (AA). Rapid and precise cell identification and classification in bone marrow smears is achieved by the You Only Look Once (YOLO) model, which is based on convolutional neural networks. This approach was used to evaluate cells from MDS-morphological bone marrow smears in 2020¹⁰

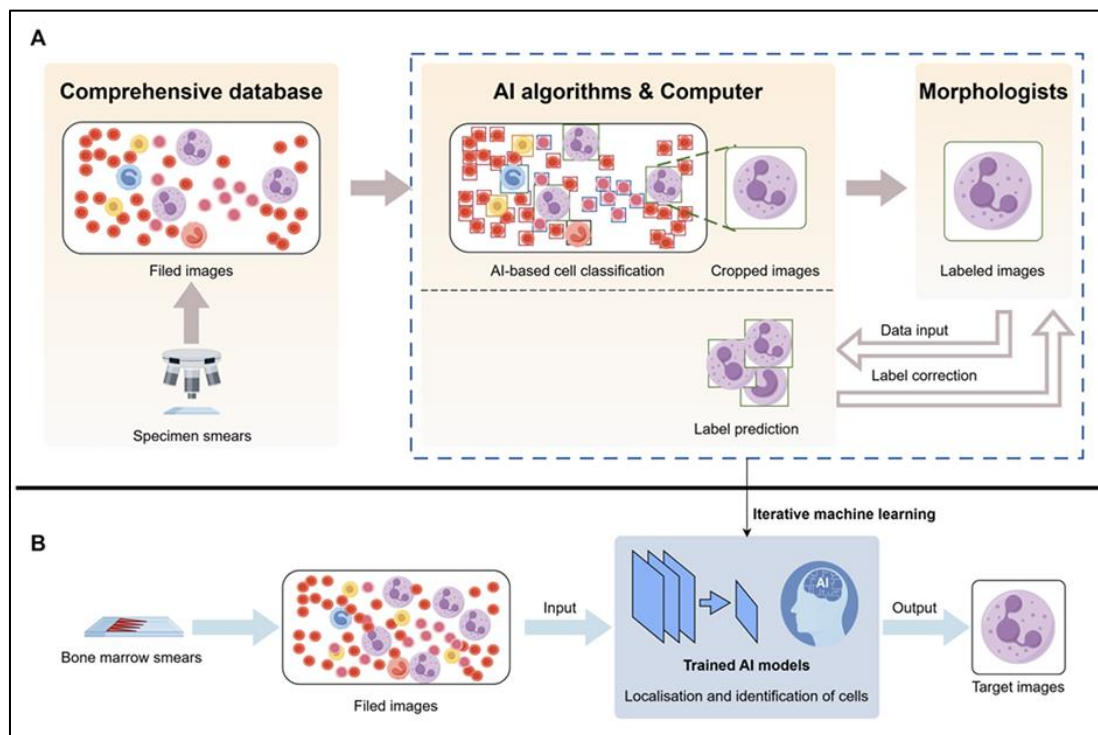


Figure 1 A. Neutrophils are detected in bone marrow smears by AI. Images of bone marrow smears in their raw form were extracted from a database. The neutrophils were snipped by an AI software, and a morphologist fine-tuned the process after multiple rounds. **B.** Raw bone marrow smears, images, and an AI model built through repetitive machine learning are utilised to generate neutrophils

To improve accuracy, Wang et al.¹¹ developed a novel YOLOX-s model. A new architecture called MLFL-Net that uses multi-level features outperformed all existing relevant models and manual experts, achieving an overall accuracy of 89.53% and a specific accuracy of 92.5% in the diagnosis and prediction of acute leukaemia within the cohort. In 2024, digital microscopy equipment was enhanced with a single-trial detection architecture based on the MobileNet V2 backbone.

The primary improvement over previous AI-based bone marrow smear analysis systems is this one's potential to remotely evaluate and exchange data, as well as its high reproducibility. By using a simple digital platform, this innovative method enhances the hospital's human-computer interface and does away with complicated medical electronic gadgets, figure 1¹²

When it comes to detecting leukemia subtypes, CNNs are superior to naive Bayes, support vector machines (SVMs), k-nearest neighbors, and decision trees¹³. By combining them with CNN architecture, newer methods such as Cat-Swarm Optimization enhance CNN performance. Modern studies back early leukemia detection techniques that use either multi-algorithms or accurate single-algorithms. Among the several types of artificial neural networks, feed-forward neural networks, ResNet-18, and AlexNet are the most accurate in diagnosing leukemia¹⁴. These techniques can detect morphological traits and foretell gene mutations, such as the NPM1 mutation that causes AML¹⁵. Clinical hematological diagnosis could be made more efficient and accurate with the help of CNN models due to their great numerical precision. This points to a fresh way of enhancing CNN models for use in therapeutic settings.

Peripheral blood smears play a significant role in the morphological diagnosis in hematopathology. There is a need for human intervention because the current digital cell imaging methods can only evaluate tiny portions of these smears. ML has allowed several digital pathology applications used in haematology to be able to gather and extract data from peripheral blood smears. To increase the efficacy and precision of diagnoses, these systems mimic cognitive modelling and manual recognition processes¹⁶. There have been advancements in diagnostic technologies such as CellaVision and computer-assisted peripheral blood smear analysis. These innovations improve the efficiency of the hematopathology lab, which in turn shortens the turnaround time for patients. Hematological diagnostics are enhanced by automating the analytical process and delivering rapid, precise results. The Scopio Labs X100, is a state-of-the-art digital microscopy imaging system that employs artificial intelligence to classify and identify blood cells in peripheral blood smears. The digital format allows for remote access by clinicians¹⁷. Another company that offers remote viewing is Techcyte Inc. in Orem, UT¹⁸. These methods gradually enhance leukemia cancer detection while drastically decreasing the time it takes to complete clinical tasks¹⁹. In comparison to traditional morphological analysis, a fully automated ML pipeline can objectively and rapidly assess peripheral blood smears. Companies that lack healthcare resources and expertise in hematopathology can greatly benefit from this competency²⁰.

2.2. Immunophenotypic diagnosis of hematological diseases using AI

It is vital to use flow cytometry (FC) or multiparameter flow cytometry (MFC) for the examination of bone marrow in hematological patients. Using fluorescently labelled antibodies, these high-throughput, high-sensitivity detection technologies may analyse the serial origin, degree of differentiation, and aberrant phenotypic features of hematopoietic cells by detecting antigens on their surface or within them. On the other hand, traditional FC analysis is lengthy and prone to errors because it needs the analyst to interpret the results manually. The analyst's proficiency determines the testing's sensitivity and accuracy. Results from combining computational analysis approaches with AI have been encouraging, thanks to ongoing research & development. AI-enhanced diagnostics outperform conventional methods. When it comes to hematological disorders, DL-based AI models can do more than just detect and classify cells; they may also uncover unanticipated biological correlations between the expression of FC markers and cytogenetic and molecular abnormalities, providing doctors with several differential diagnoses. Clinical diagnostic accuracy and consistency are both enhanced by automated gated analysis and state-of-the-art visualization.²³

But the MFC data used by most AI models has limitations due to panels and is frequently quirky. A clinically generalized FC panel called DeepFlow, which uses multidimensional density-phenotype coupling, has been developed recently.²⁴⁻²⁶

Cell lineage clustering and analysis can be completed in less than 5 minutes thanks to its automated response to changes in reagents and equipment.²⁷ Using RF, multidimensional clustering, DeepFlow, and unsupervised learning algorithms for leukemia classification and diagnosis is almost as accurate as human analysis²⁶. Compared to more traditional methods, this one increases the quality and standardisation of lymphocyte subpopulation classification while increasing its speed. It is believed that AI and ML will help eliminate healthcare disparities and deliver more equitable healthcare by improving the accuracy and reliability of immunological diagnoses.²⁷

Haematological disorders can be better diagnosed with the use of immunohistochemistry (IHC). The exponential increase of IHC data has rendered manual interpretation ineffective. An AI system called ImmunoGenius tackles this problem by using Bayesian theorem probabilistic decision trees. Clinical hematopathologists and haematologists will find it easier to understand IHC results with this tool, which can detect and forecast B-cell and T-cell lymphomas on both iOS and Android. Clinical AI systems need to incorporate additional diagnostic data, including histology because there aren't any discrete IHC signals and IHC profiles are converging in AI system evaluations²⁸⁻³⁰

2.2.1. Cytogenetic karyotyping for AI-enhanced hematological disease diagnosis

Multiple chromosomal anomalies are present in hematological diseases, even in individuals with the same symptoms. There are a lot of duplications, deletions, and rearrangements in hematological cancer cells. Precise anomaly interpretation is crucial for the classification, prognosis, and treatment choices of hematological cancers.

Although genetic data has enhanced our comprehension of haematological malignancies, there are still challenges when it comes to clinically using these massive, intricate, and time-consuming datasets. Haematological cytogenetic laboratory tests rely on chromosomal karyotyping. To manually categorise and construct karyotype maps of G-banded metaphase chromosomes, pathologists rely on the length and banding pattern of each chromosome. Nevertheless, this is expensive and useless.

The potential for ML to automate the interpretation of cytogenetic data has been demonstrated throughout history. Improved chromosome classification and karyotyping has led to an increase in clinical applications of AI, approaches for automated mid-cycle capture, semi-automated, or interactive karyotyping. AI-powered solutions streamline and enhance the accuracy of chromosomal karyotyping, cutting down on the time and money needed for the process.^{31,32}

In order to increase intermediate chromosome recognition and classification to 98.8%,³³ the CNN approach fixed rotation and location in standard karyotype analysis. One novel approach to accurate karyotype analysis in individuals with a wide variety of numerical abnormalities is the use of machine learning to enhance intra-karyotype interaction and category distribution for chromosomal R-and G-band categorisation³³

2.2.2. Haematological illness diagnosis with AI-enhanced molecular biology

Molecular biology assays are necessary for a thorough diagnosis of haematological diseases. Through the examination of leukaemia cell genes and mutations—particularly those that may induce illness start or regression—molecular analysis of blood, encompassing polymerase chain reaction, DNA sequencing, transgenics, and gene chip technology, can forecast and detect disease development.

In order to prioritise genetic variants for automated disease categorisation and clinical decision-making, functional genomics necessitates massive amounts of data to annotate biologically relevant genomic areas and their therapeutic implications. Sequencing gene sections linked to a suspected disease is the subject of ongoing research with the goals of reducing costs and increasing efficiency.

The diagnosis and treatment of AML requires whole-genome sequencing. The use of predictive genetic signatures, high-dimensional ML data, and sophisticated deep neural networks can accomplish AML subtyping, differential diagnosis, and risk prediction. Reference blood gene expression profiling datasets with a large number of samples work best for AML classifiers since the accuracy of the classifiers is directly correlated with the size of the samples. Costs can be reduced and shortages of experts in certain areas or medical settings can be addressed with this strategy. Gene prediction approaches linked to AML, like many models, use binary classification to differentiate between genes that have been identified as causal and those that have not. A one-class support vector machine (SVM) AML classifier dedicated to genes was developed³⁴ The reduced error rate of gene expression profiling made possible by AI makes it a superior clinical tool to binary classification models in terms of efficiency, objectivity, robustness, and predictive power.

There has been recent evidence connecting DNA methylation (DNAm) to the development and advancement of cancer. Adding methyl groups to nucleotides, primarily at cytosine-guanine dinucleotides, does not alter their sequence; this process is known as DNA methylation. Hypermethylation of tumor suppressor genes and hypomethylation of oncogenes may contribute to the poor prognosis in hematological cancers including acute lymphoblastic leukemia and MDS. Processing genetic data is laborious due to the many hypotheses testing and covariate management required for conventional phenotype heterogeneity analysis. But deep learning can find and assess DNA methylation on actionable genomic targets, according to a number of AI algorithms and applications. The detection of hematological diseases is aided by this³⁵ In order to decrease the expense of inferring DNA methylation variations in patients with acute

lymphoblastic leukemia, Teschendorff et al. ³⁶ developed EPISCORE, a reference model for single-cell histology that employs deep learning algorithms to analyse DNA methylation cell heterogeneity using high-resolution datasets ³⁷ MethylNet is an additional deep learning model that seeks out previously unseen patterns of DNA methylation by employing unsupervised generation, grouping, cell type deconvolution, subtype classification, age regression, alongside smoking status classification. One more perk is how easy it is to use.

The growing accessibility of genetic data has made next-generation sequencing (NGS) essential for precise diagnosis and treatment in clinical cancer and hematology. A semi-automated artificial intelligence pipeline for clinical sequencing and precision medicine in hematological malignancies, Watson for Genomics (WfG) was built utilising proprietary natural language processing methods. In order to examine sequencing data, find mutations and pathways, and find out drug information from more than 150 patients' benign and malignant tissues, Tojo ³⁸ utilised WfG. To show how AI might help with human interpretation, Yokoyama ³⁹⁻⁴² used clinical sequencing data from more than 300 hematological malignancies.

The current method of hematological diagnosis is under threat from whole-genome sequencing and next-generation sequencing that incorporates artificial intelligence ^{40,43-45} Artificial intelligence outperforms hematologists in interpreting high-dimensional whole-genome sequencing and next-generation sequencing data, which improves diagnostic accuracy, speeds up diagnosis, and decreases interobserver variability. Healthcare decision-makers will also increasingly rely on AI-assisted genomic analysis. Due to the paucity of genome-wide data, it is challenging to use DNA sequence data alone to forecast chromatin connections across open chromatin patches. As ChINN can identify open chromatin connections across the entire genome, it is a practical approach. Uneven oncogene expression was suggested by the data from CLL patients, who exhibited substantial heterogeneity in prognostic gene chromatin interactions ^{41,45-49}

Table 1 Performance metrics of AI applications in Hematopathology diagnosis

Application	Performance	Reference
Classification of mature B-cell neoplasm	Accuracy: 95% 10% validation split	50
Detection of immature leukocytes and their classification into 4 types	Accuracy: 92.99%	51
Identification of the leukemia type based on patient genetic expression	Random forest accuracy: 80.8% XGBoost accuracy: 92.3 Internal validation 65%/35% split)	52
Classification of lymphocytic cells	Accuracy: 94.94%-96.25% Validation on an external independent clinical trial	53
Detection of leukemia and its types	Accuracy: Above 80%	54
Automated detection of malignant lymphoma	Accuracy: 97% K-fold cross validation repeated 5 times	55
Multiclassification of leukemia	Accuracy: 97.7% Internal validation (90 images used for training and 10 kept for validation)	56
Leukemia and lymphoma diagnosis	Correctness: 95% 30-fold cross validation	57
Determining the most predictive features for acute lymphoblastic leukemia identification	Accuracy 87.4% internal validation (train/validation data) 10-fold cross validation	58
Leukemia diagnosis and its subtypes	Accuracy: 97.8%	59

2.3. Integration of AI in laboratory information systems

AI systems utilize sophisticated algorithms to process big data. This means quicker, more confident decision making - supporting pathologists in identifying even the smallest areas of suspicious tissue. Repetitive tasks such as data entry and analysis of your slides can be automated, helping you to streamline workflows. It minimizes the risk of human error and far more importantly enhances patient outcomes. Moreover, this AI-assisted analysis helps in predictive biomarker discovery and tailored treatment selection to improve patient care ^{5,42} The ongoing digitalization of laboratory practices again emphasizes the need for co-development of centralized platforms that would enable more data sharing and joint innovations in diagnostic tests as proposed ^{43,44}. AI not only excels in providing better diagnostics but it is changing the educational paradigms for lab learning.

3. Benefits of AI in Hematopathology

Artificial intelligence in hematopathology has massive benefits. Therefore they are able to see small visual anomalies which can evade a human⁴². Very desirable in the case of illnesses such as leukemia which demand speedy detection and high accuracy in medication administration. But AI systems can scour now huge databanks With commonsense aplomb. This translates into business that is even more efficient and faster, no trivial matter when you are performing procedures on patients ⁴⁵. see also here, What used to be considered a monumental task in the past can now be done much faster through automated processes. This allows experts to focus their knowledge in areas that they are most required ⁵. These AIs not only positively influence the accuracy of the diagnosis but also enable the patient outcomes, which implies a paradigm shift in the theater of hematopathology ^{43,44}.

3.1. Increased diagnostic accuracy

AI enables more precise diagnosing and treatment plans. AI-based algorithms applied to hematological images are helpful in, dominate to detect minute, difficult to find that an observer may neglect, so improving the precision of diagnostic outputs ⁴⁴. For example, deep learning in the context of image analysis allows for better interpretation of blood smears and biopsy samples, thereby enhancing pathologist ability to classify conditions. Well, standardised diagnostic processes are reinforced even further, reducing human error and shaping variability by removing cumbersome manual processes.⁴⁶ The ability of AI to identify novel biomarkers or genetic alterations that provide insight into the disease and can also be utilized to optimize treatment strategies makes this a very important development, ^{5,42,44} The ability of AI to identify novel biomarkers or genetic alterations that provide insight into the disease and can also be utilized to optimize treatment strategies makes this a very important development, ^{27,46} In the domain of hematopathology the benefit of these technologies is not just in diagnosis but also in overall patient management, figure 2.

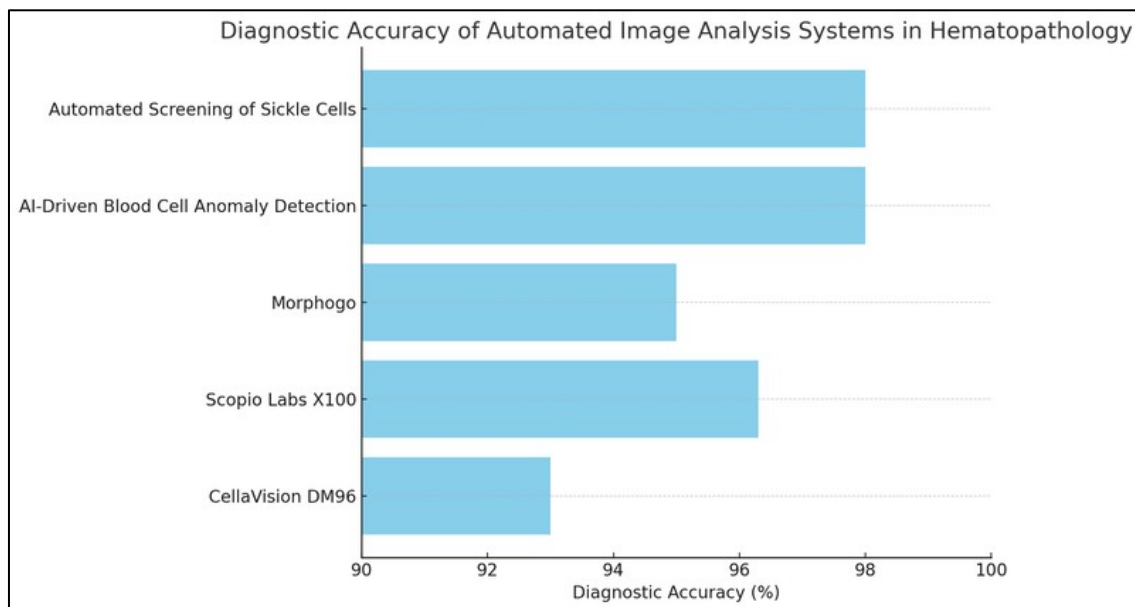


Figure 2 This chart displays the diagnostic accuracy of various automated image analysis systems used in hematopathology. All systems show high accuracy, with "AI-Driven Blood Cell Anomaly Detection" and "Automated Screening of Sickie Cells" both achieving the highest accuracy of 98%.

3.2. Reduction in turnaround time for results

For diagnosing things, especially difficult cases, such as blood cancers, laboratory workflows have been significantly accelerated with the help of ML, researches show that AI can analyze all types of biological information, such as images and cell samples, with significantly reduced processing times while maintaining diagnostic accuracy of the diagnosis⁴⁸. Such as CNNs diverse predication models can perform quick detections of the basic chromosome defects, therefore decreasing manual efforts⁵. However, with advancements in AI, that means more opportunities for doctors to work with patients on treatment decisions. This drives more timely patient appropriate/nice care sooner and, on a system capacity degree, larger access to healthcare for everyone⁴⁷, figure 3.

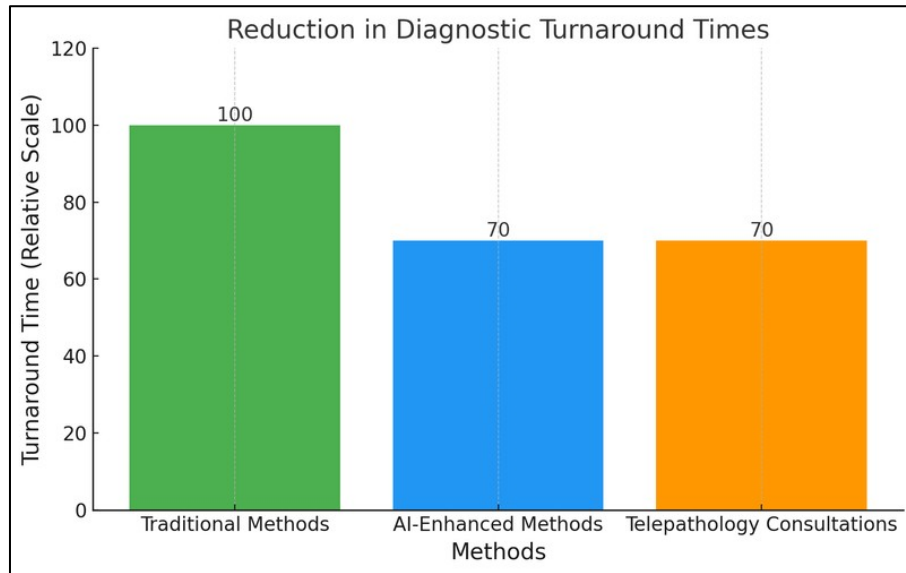


Figure 3 Comparison in diagnostic turnaround times for hematopathology methods. Traditional methods have the longest turnaround time, while both AI-enhanced methods and telepathology consultations show significant improvements, reducing the turnaround time

3.3. Enhanced workflow efficiency in laboratories

It is therefore becoming apparent that the enhancement of the hematopathology labs are essential to us in terms of offering superior diagnosis and ultimately superior results in our patients. Integration of AI into this is one of the ways. Many stages are involved in preparing tissue sections and analyzing samples, as well as analyzing and interpreting data, which AI is able to decrease the manual workload. This is not the only one, it minimizes the time it takes to turn out the results and possibilities of errors can be reduced. The act of zooming in provides free hands to the individuals who had to deal with automated systems and AI technology in order to save attention and energy on the most complicated cases rather than the routine analysis⁴². Similarly, these technologies enable professionals to consult with one another, which may also be internationalized therefore, exchange of expertise of professionals⁴⁸. Notably, embedding an ML algorithm into a workflow of detecting such structural chromosomal abnormalities, this may be performed in a significantly smaller time scale that can acquit clinical FC⁵. This is not merely a more effective lab as Broadly puts it, this implies that patients will experience higher level of customized high-beam care. In most instances, this change is already impacting the work of the practice of hematopathology in a very real manner.

3.4. Support for pathologists in decision-making

AI applications enable have enabled pathologists to access large datasets, enhancing both diagnostic accuracy and operational efficiency. By processing repetitive workloads and rapidly analyzing images, AI aids clinicians in identifying subtle anomalies that could otherwise be overlooked, thereby reducing diagnostic error rates. Furthermore, through AI integration it supports the implementation of standardized diagnostic criteria that generates consistency of decision-making throughout the institutions⁴². The importance of uniformity only increases when pathologists encounter challenging cases where they must make decisions with the best patient outcomes in mind. AI-powered collaborative networks play a critical role in promoting knowledge exchange and continuous professional development among pathologists.⁴⁴

3.5. Cost-effectiveness of AI solutions

AI programs have the ability to rapidly analyze vast quantities of data, drastically reducing the time doctors take for routine check-ups, freeing up their time for more complex cases. Moreover, AI with digital pathology installations, enhances the performance of these systems by improving telepathology ⁴⁶. With this new procedure, it eliminates geographical barriers and allows more people to access professional assessments. This demonstrates that investment in AI tech pays off. With advancements in digital pathology, it is becoming apparent that the future of blood-disease pathology requires imminent implementation of AI in hospitals and clinics.

4. Challenges and Limitations of AI in Hematopathology

Although, the AI promises in the hematopathology area are alluring, there are a number of critical issues that need to be addressed in order to hasten its adoption. AI has great technical, methodological, and systemic drawbacks. Preanalytical issues also play a significant role in the performance of models-based on the variation in staining, imaging procedures and sample preparation, a poor translation of models into practice is achieved. The failure to misclassify, particularly similar or rare cell types, and other issues with the automated high-throughput workflow are reported by various studies with up to 9.5% of the cases failing to be processed.

Though algorithms work well under controlled conditions, they require re-calibration as well as additional local validation to be implemented in clinical settings. Some issues of data quality and standardization are also explained in papers. This is due to the fact that unavailability of datasets that are not only diverse but are also large and are continuously being annotated would result in low external validity and inconsistent inter-institutional results.

In addition, the models are black box, which leads to poor explainability and low uptake by clinicians. Now the evidence shows that they are to be considered as complementary factors and not as a substitute to expert assessment of specimens by the hematopathology. Without much attention to the quantity of the data that is cleaned and organized, one will come across the issues: AI systems perform best when the data to learn and work with is correct and clean and well-contained, and there are difficulties when working with old data it was contaminated with, or the data is sporadic, or it is improper, and this can lead to a misdiagnosis ⁴². However, there are the rules and ethical issues, like the way to secure confidential information and the ethical authority, making it still more difficult to implement AI in clinics ⁴³. To make the situation even more bewildered, questions about funding and resources are also present on how many AI systems can be adopted as the digital pathology is still being enhanced ⁴⁵ to support the argument that the AI issues concerns need to be integrated in practical clinical settings, the corresponding figure is provided.

4.1. Data quality and availability issues

To be useful in digital pathology, AI systems require high data quality and structure to act as it is in the extraction and management of data. Bad data will cause bad results because faulty diagnoses will be the outcome of bad data. Histologization of the histological slides is a big step but that would need a standardization of the variation both in the quality of the images and the files. These differences may make the work of AI algorithms difficult ⁴². The presentation of variants of data, i. e. patient clinical history and their genomic data results in problems of interoperability and privacy of data. This directly affects the availability of the datasets needed to be analyzed ⁴⁴. This is to say that better AI is dependent on complete datasets and effective image analysis techniques. AI systems should address such obstacles to quality and availability of data to facilitate hematopathology. ^{5,42}

4.2. Ethical considerations in AI deployment

Ethical issues are to be handled carefully. The privacy of patients, especially, is a significant issue related to the manner in which AI algorithms process sensitive health data. This highlights the significance of informed consent whereby the patients are to be well aware of how their data can be utilized to enhance diagnosis as well as research purposes. We should also not ignore the possibility of AI algorithms being biased. Prejudicial data may even cause further differences in health care and therefore worsen the already existing healthcare differences ⁵, raises the need to use varying data sets to reduce such a risk.

AI decision-making requires transparency to empower the healthcare workers to understand the findings and have confidence in them. However, this form of transparency is also as it has been observed by prior research ⁴³, what actually allows the and truly beneficial collaborative models of diagnostic systems using human judgment and AI systems - the so-called computational-assisted diagnostic accuracy, and better patient management. Finally, the ethical implementation of AI in clinical hematopathology is an action that needs a complex strategy.

4.3. Resistance to change among healthcare professionals

Still, there are many healthcare practitioners unready to embrace AI in healthcare facilities especially in an area such as hematopathology. Healthcare workers fear losing their jobs, lack familiarity and awareness on the functionality of the systems, and how they will interfere and alter standard processes. This form of contradictory power can, nevertheless, negatively affect the advantages of AI or inhibit its adoption like specific diagnosis and streamlined procedures⁴². Integration with AI affects the fundamental ways of doing things, so it is quite understandable that people think about liability and reliability as well⁵. It typically requires a significant efforts to get the implementation of these AI technologies, which could help predict outcomes, identify diseases, ... must be tailored to diverse clinical contexts⁴⁹. Addressing these concerns directly, through the development of educational programs and demonstration studies that show the practical benefits of AI, might facilitate the adoption process and ultimately improve patient outcomes in hematopathology⁴⁵. In doing so, Visual tools can also support the transition by illustrating how AI integrates into routine diagnostic workflows of how AI is likely to enhance traditional processes and normalise the change it brings by illustrating the operation of diagnostic routines.

4.4. Regulatory hurdles and compliance

The current healthcare standards are largely centered on the three most valuable concepts of patient safety, quality control and data privacy (These principles, though essential, also present major compliance issue in attempts to comply). To make this situation even more difficult, these rules differ depending on where one is. To attain the best quality, practitioners must be knowledgeable of a number of local and international standards. The challenge in creating AI tools is that it requires them to undergo clinical trials. Lax rules will slow the adoption of AI, especially at initial stages.

AI systems usually demand huge quantities of high-quality data to learn and validate, which cannot always be available in the case of hematopathology^{5,42}. When rare blood disorders can be considered as an example, limited data may cause biased results or lower reliability of the models, or merely cannot get similar results. The other problem with AI technology is the standardization, privacy of data and regulatory demands of the integration into the current workflow^{43,44}.

4.5. Future Prospects of AI in Hematopathology

The ongoing development of AI, can lead to the further development of hematopathology in a way that we did not think of that much. With the further development of the AI integration, we can observe significant progress. Specifically, more complicated algorithms might assist in interpreting complex hematological images, and perhaps in more detail than previously. Automation of some routine chores would be another method of reducing errors and maximizing the output of a pathologist, and AI is a good offer. It would then make them have time to work on complex or atypical cases. In addition, AI-based predictive analysis allows personalized patient care in patient care. This kind of analytics can possibly make it possible to predict the patient reaction to the treatment in regard to personal genotypes and other characteristics of the given disease⁴⁵. However, there are also certain aspects that we need to solve, primarily, to ensure the solid data security as the imaging technologies will become more and more digital⁴⁴. The integration of imaging technologies and data strategies will need to happen along with the development of AI, which will become increasingly important as the future of hematopathology, not only to the perspective of diagnostic accuracy and patient outcomes, but also to the point in which AI will be an indispensable and more necessary tool in this important field of medicine.

4.6. Potential for personalized medicine applications

With the introduction of the artificial intelligence (AI) into the field of hematopathology, the future of personalized medicine has become a reality, as the means of diagnosing and treating our patients, as well as treating our patients. Doctors can inform bespoke treatment strategies based on the patient profile of an individual patient in order to eventually optimize clinical outcome and toxicity. Use can increase risk stratification and targeted therapy choice that can allow more personalized therapeutics of the blood malignancies. Moreover, machine learning can identify new biomarkers that can be useful in treatment planning, allowing more personalized treatment of patients that address the complexity of blood disorders, and can be used to improve patient care overall.

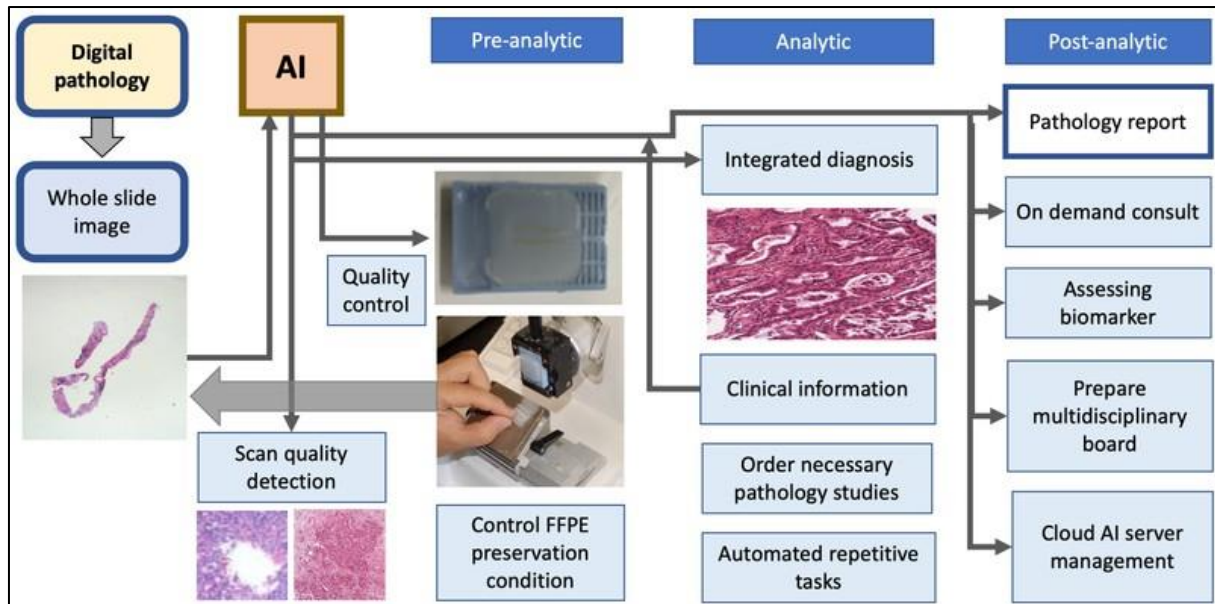


Figure 4 Integration of AI in Digital Pathology Processes

4.7. Integration of AI with genomic data

Based on machine learning (ML), AI analyzes sophisticated genomic data and defines gene mutations and expression trends linked to 8042 blood cancers. This helps in risk stratification and treatment decision making and this allows the individualized therapies which could help in leading to better clinical outcomes. In addition, AI is able to work with large volumes of data, thus, genomic data can be constantly updated according to the latest scientific discoveries⁴⁵. Artificial intelligence implementation in combination with the fast-increasing genomic information catalyzes the diagnostics and deepens our knowledge of the biology of the disease, as recent research of Philadelphia-negative MDS shows. This integration will be redefining diagnostic and treatment approaches in hematopathology in the event that a new paradigm of patient care should be formed, more generally⁵.

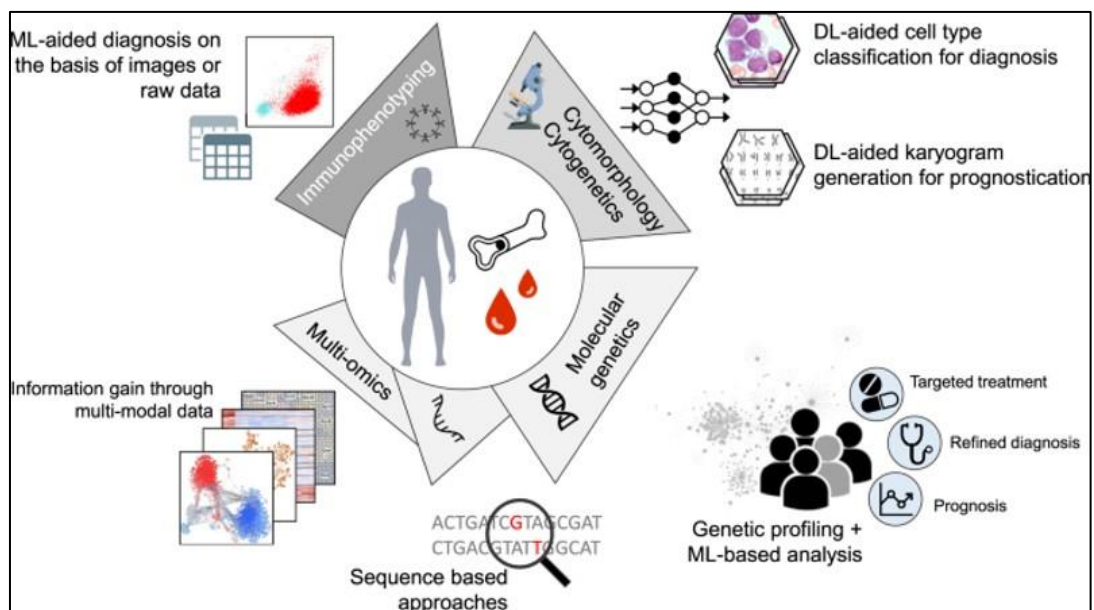


Figure 5 Integration of Machine Learning and Deep Learning in Healthcare Diagnostics and Prognostics

4.8. Role of AI in telepathology

Telepathology involves technology to improve remote consultations, but AI can be used to accelerate the rate at which it is prepared since the consumption of the tissue sample takes place, until the moment of the diagnosis is achieved,

which is more reliable and allows pathologists to reach diagnostic conclusions even when they are not in that location. AI will be integrated well into telepathology because, AI by processing vast quantities of data and identifying pathologic details within pathology images that humans are prone to ignore can not only guarantee a more efficient process but also a more cooperative and convenient diagnostic setting ^{5,24,44}

4.9. Predictions for AI's impact on future hematopathology practices

The transformative purpose of the AI in the field of hematopathology is gaining more and more recognition. It is probable that advanced ML algorithms will be entrenched in the future practices. These algorithms can enhance the diagnostic processes by analyzing complex biological data-based on morphologic images and flow cytometry results more quickly and more accurately. Convolutional neural networks (CNNs) have played a major role in this transformation and have been spearheaded by CNNs. These networks have the potential to identify the various kinds of repeat chromosomal abnormalities in conditions like AML that can result in the completely automated diagnosis. Moreover, the developing opportunities of AI can bring major improvements to the spheres of distance consultations and co-networks of pathologists. This might help to enhance the exchange of information on the international level and the unification in diagnostics ⁴². All of this augers well with the implementation of AI, and the discipline is projected to be more dependent on such technology in the future to enhance patient care through greater diagnostic opportunities in the future in the area of hematopathology ⁴⁴.

5. Conclusion

In hematopathology, AI can help speed work, make diagnoses more accurate, and even help tailor treatments to the individual. AI's ability to crunch huge datasets fits nicely with things like telepathology and virtual microscopy, which could open doors for doctors to work together on diagnoses more easily

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