International Journal of Creative and Open Research in Engineering and Management
ISSN: **3108-1754 (Online)**
Volume 02 Issue 08 Augustl-2026 | Impact Factor: 3.5

Integration of Artificial Intelligence and Digital Morphology in Haematology Laboratories: A Comprehensive Review for Clinical Practice and Future Horizons

Mr. Nasib Ali
Assistant Professor,USTM
Seleibam Monojit Sen
Assistant Professor,USTM
Rabina Bariam
Assistant Professor,USTM
Sanda Jingieid Kharngi
Assistant Professor,USTM
Md. Noor Habib
Assistant Professor,USTM
Dr. Amirul Hassan Barbhuiya
Principal, Associate Professor, Allied Medical sciences USTM
Affiliation: Department of Medical Laboratory Technology
University of Science and technology of Meghalaya, Ri-Bhoi, Meghalaya793101
Email: nasib8472@gmail.com

How to Cite this Article:

Ali, N., Sen, S. M., Bariam, R., Kharngi, S. J. & Habib, M. N. (2026). Integration of Artificial Intelligence and Digital Morphology in Haematology Laboratories: A Comprehensive Review for Clinical Practice and Future Horizons. International Journal of Creative and Open Research in Engineering and Management, 02(8), 1-9. https://doi.org/10.55041/ijcope.v2i8.004

Abstract:

The morphological evaluation of blood and bone-marrow smears remains an essential component of Haematology diagnostics despite the significant growth of automated Haematology analyser s. The advent of digital slide imaging (digital morphology) and artificial intelligence (AI) driven image analysis offers a transformative opportunity to increase efficiency, consistency, and diagnostic precision in Haematology laboratories. This review provides a detailed examination of the evolution of Haematology diagnostics, current AI methodologies in cell classification, slide digitisation technologies, real-world clinical applications, validation and regulatory considerations, and future directions including the role of AI in personalised medicine. The evidence demonstrates notable benefits improved turnaround times, enhanced accuracy, remote review capability but also underscores critical challenges: slide quality dependence, algorithmic limitations with rare and abnormal cells, data standardisation, validation and regulatory frameworks. For laboratories seeking to adopt AI-integrated digital morphology, a hybrid human-AI workflow with robust validation and ongoing performance monitoring is currently the most pragmatic route. Emerging trends such as foundation models, multimodal integration and federated learning suggest that the future Haematology laboratory may be highly digital, adaptive and personalised yet human expertise remains indispensable.

Keywords: Haematology, digital morphology, artificial intelligence, machine learning, deep learning, slide scanning, cell classification, laboratory automation, validation, personalised medicine.

1. Introduction

The field of Haematology diagnostics has undergone dramatic change over the past few decades. Quantitative automated Haematology analyser s now routinely perform complete blood counts (CBCs) with differential, reticulocyte counts, and many flag abnormal populations. Nonetheless, the morphological review of stained peripheral blood and bone marrow specimens remains essential for the detection of blasts, dysplastic cells, rare populations (e.g., circulating tumour cells, parasite infected red cells), evaluation of red-cell or platelet morphology, and confirmation of analyser flags. Manual microscopy, however, is labour intensive, time consuming and suffers from inter and intra-observer variability (Kratz et al., 2019).

Simultaneously, digital imaging and computer vision advances have matured. High resolution slide scanners, networked storage, and advances in machine learning (ML) and deep learning (DL) now make it feasible to digitise whole blood (or marrow) slides and apply automated image-analysis workflows. The term “digital morphology” (DM) commonly refers to such digitised slide workflows in Haematology laboratories, often coupled with AI based pre-classification of cells (Kratz et al., 2019).

The combination of AI + digital morphology holds the promise of improved diagnostic precision, faster turnaround, reduced labour burden, better archiving and remote review capacity. However, the actual implementation in Haematology laboratories raises many practical, technical, regulatory and educational questions. This review therefore: (1) describes current AI methodologies for cell classification; (2) examines slide digitisation technologies and workflow impacts; (3) discusses clinical applications, benefits and challenges; (4) outlines validation and regulatory frameworks; and (5) explores future directions including personalised medicine in Haematology. The aim is to provide laboratory managers, clinical instructors and Haematology professionals with an authoritative resource guiding adoption and future planning.

2. AI in Cell Classification

The core of AI integration in digital morphology is the automated identification, segmentation and classification of cells (or fields) from digitised slides. This section analyses current methodologies and evidence, as well as strengths, limitations and practical issues.

2.1 Methodological overview

Traditional machine-learning approaches. Early digital morphology systems leveraged handcrafted features: size, shape, nuclear/cytoplasmic ratio, texture, colour histograms, granularity. These features were input into classifiers such as support vector machines (SVMs), decision trees or random forests. While these methods had some success, they required substantial feature engineering, struggled with morphological variability (especially in abnormal cells) and often lacked scalability.

Deep learning / convolutional neural networks (CNNs). More recently, the application of CNNs has revolutionised image-based classification workflows because they learn discriminative features directly from large annotated image sets, avoiding manual feature-engineering. For instance, in a study of 102 blood samples the authors used a CNN model to pre classify leukocytes, resulting in improved accuracy and shorter review times for technologists. Other research such as the “Dino Bloom” foundation model (Koch et al., 2024) reveals that large pretrained cell image models may enhance generalisability across sites/labs.

Segmentation + classification workflows. Many systems decompose the problem into (a) cell (or region) detection/segmentation and (b) classification of detected objects (e.g., neutrophil, lymphocyte, blast, dysplastic cell).

Some advanced workflows perform end-to-end learning (region detection + classification) in one pipeline (Moosavi Tayebi et al., 2021) for bone marrow cytology.

Weak supervision, transfer learning and anomaly detection. Given the scarcity of annotated images for rare or abnormal cells, models increasingly employ weakly labelled (slide level) data, transfer learning from natural image domains, and anomaly detection frameworks (detect "unusual" cells rather than pre classify all). These approaches attempt to mitigate annotation bottlenecks and domain shifts (e.g., different stain, microscope, site).

2.2 Performance and evidence

One significant study (Xing et al., 2023) found that junior technologists' accuracy of leukocyte classification increased by ~4.8 % (normal cells) and ~15.2 % (abnormal cells) when using AI assistance, with an average time reduction of ~215 s per smear. A performance evaluation of the Sysmex DI 60 digital morphology analyser (Zhao et al., 2024) found good correlation for neutrophils, blasts and lymphocytes (r = 0.94, 0.80, 0.85 respectively) but weaker performance for monocytes, basophils and plasma cells; performance also degraded in moderate/severe leucocytosis or leukopenia.

A meta-analysis of AI in digital pathology (though not Haematology-specific) demonstrated mean sensitivity ~96.3 % and specificity ~93.3 % across applications but emphasised large heterogeneity and bias in studies.

2.3 Strengths and opportunities

- Speed and efficiency: Automated pre classification speeds review, prioritises flagged/abnormal cells and reduces manual burden.
- Consistency and reproducibility: AI derived classification is less subject to human variability, especially across technologists or shifts.
- Scalability: Once trained and validated, AI can handle large volumes of digitised slides, enabling centralised review in large labs or networks.
- New capabilities: Analytics beyond classification (e.g., morphological feature extraction over time, integration with other data) become possible.

2.4 Challenges and limitations

- Rare/abnormal cell types: AI models still struggle with dysplastic cells, plasma cells, very low/high WBC counts, overlapping cells or poor smears. e.g., plasma cells had Kappa ~0.27 in the Zhao et al. study.
- Data and annotation bottlenecks: Building training sets of sufficient size, diversity (stain/microscope/site variation), especially for abnormalities, remains difficult.
- Domain shift: Differences in microscope optics, stain quality, smear preparation and camera hardware may degrade model performance when deployed across labs.
- Interpretability and trust: Many deep models are "black boxes"; labs may be reluctant to rely on them without transparency or explanation of classification decisions.
- Workflow integration: AI must integrate with lab information systems (LIS), image management, reporting workflows. Technical, logistic and human factors issues remain.
- Validation and regulatory oversight: AI for morphology falls under evolving regulatory frameworks, which labs must navigate carefully (see Section 5).

Challenge	**Why It Happens**	**Impact on Lab**
Rare cell types	Not enough training images	Misclassification
Domain shift	Different stains, microscopes	Reduced accuracy
Overlapping cells	Hard for segmentation	Wrong identification
Poor smear quality	Input dependent	AI failure, false negatives

Extreme WBC counts	Out-of-distribution samples	Algorithm instability
Black-box nature	Deep learning opacity	Trust + regulatory issues

2.5 Summary

AI-driven cell classification in Haematology is no longer purely experimental—it is now entering routine workflows for peripheral blood smears in many laboratories. The evidence shows improved accuracy and efficiency under certain conditions. However, significant gaps remain—especially for abnormal morphology, rare cell types, diverse slide preparations and cross-site generalisability. For implementation, laboratories must adopt a hybrid workflow (AI assisted, human review) with ongoing monitoring and quality control.

3. Slide Digitisation Technologies

To enable the AI workflows described above, robust digital slide acquisition, image storage, and workflow integration are required. This section reviews the major components: slide scanning (whole slide imaging or selected fields), image acquisition/processing, archival/storage, and workflow implications for Haematology labs.

3.1 Slide scanning and whole-slide imaging (WSI)

Traditionally, morphology review in Haematology is performed on glass slides via microscope. Digital morphology replaces or complements this by scanning slides to generate digital images of either selected fields or the entire slide (a whole slide image). The International Council for Standardization in Haematology (ICSH) review (2019) noted that digital morphology analyser s now exist from several manufacturers, yet standardisation of slide preparation, magnification, colour/displays and file formats remains a weakness.

Some platforms focus on “cell locating” (scanning and imaging discrete candidate fields or cells), while others scan full peripheral blood smears at high magnification (100× equivalent), enabling zoom/pan similar to microscopy but with digital advantages.

3.2 Image acquisition & processing

Key steps and considerations include:

- Slide preparation & staining: smear quality (monolayer, minimal overlaps, proper stain) remains critical. DM performance degrades with poor input quality.
- Scan resolution/focus: High-magnification imaging (e.g., 100×) and focus-stacking may be required to capture cytoplasmic granules and nuclear detail. Many scanners incorporate automatic focus detection and multi-plane imaging.
- Colour calibration and display: Digital images must maintain accurate colour (chromatin, cytoplasm granules, RBC inclusions), brightness, and contrast. Variation across hardware can affect classification. ICSH noted differences in colour and display qualities across instruments.
- File formats, compression, and storage: Digital slides are often large, sometimes several gigabytes. Compression should find a balance between storage and image quality. Metadata, including patient ID, smear type, and magnification, must be kept intact.
- Cell locating and segmentation: Some systems automatically identify candidate cells or fields before classification; however, segmentation accuracy is still a challenge for overlapping or abnormal morphologies.
- Integration with LIS and PACS: Digitized morphology images and AI outputs need to fit into the laboratory workflow, including report generation, image archiving, remote review, and quality control or training.

3.3 Digital storage, networking and remote review

One of the key advantages of digital morphology is remote review and archive capability. Slides (or candidate field images) can be stored, shared across sites for consults, archived for training/QC and retrieved for second look. The ICSH review highlighted the use of digital image archives for quality assurance, training, competency assessment and remote consultation.

Network infrastructure, secure storage, user-access control, data retention policies and backup/disaster recovery all become critical operational components for digital morphology systems.

3.4 Impact on workflow efficiency and diagnostic precision

One of the main benefits of digital morphology is the ability to review and archive data remotely. Slides or candidate field images can be stored and shared across locations for consultations. They can also be archived for training and quality control, and easily retrieved for a second look. The ICSH review emphasized the importance of digital image archives for quality assurance, training, competency assessment, and remote consultations.

Network infrastructure, secure storage, user access control, data retention policies, and backup and disaster recovery are all crucial parts of digital morphology systems.

Feature	**Manual Microscopy**	**Digital Morphology**	**AI-Assisted Digital Morphology**
Review Speed	Slow	Moderate	Fastest
Inter-observer Variability	High	Moderate	Low
Remote Review	Not possible	Possible	Possible
Detection of Rare/Abnormal Cells	Depends on expertise	Improved with archived zoom	Best when reviewed + AI flags
Consistency	Variable	Good	Very High
Initial Cost	Low	Medium–High	High
Best Use Case	Routine labs, low volume	Teaching, archiving	High-volume labs needing speed

Adopting digital morphology, particularly when paired with AI, has shown improvements in workflow:

• Shorter review time: as noted in Xing et al. (2023) with an average time savings of about 3.6 minutes per smear.

• Improved consistency and archiving: digital images enable the review of flagged cases, track morphology over time, and reuse for teaching and training.

• Remote triage and consultation: labs with lower volumes or in remote locations can use central reviews, helping address workforce challenges.

• Better integration of morphological data with other digital lab data, like CBC, flow, and molecular data, allowing for more complete diagnostics.

However, initial costs for the slide scanner, storage, and network, along with staff training and workflow redesign for scanning, image quality control, and human review of AI outputs, remain obstacles.

3.5 Technical and operational considerations

• Slide quality is crucial. Automated scanning or AI cannot make up for bad smear preparation or staining. Quality management of smear prep is essential.

• Calibration and validation of scanners are important. Focus, colour, and magnification must be checked regularly. Labs should track scanner performance and watch for drift.

• Interoperability and standardization are key issues. File formats, image metadata, and integrations with LIS/PACS vary among vendors. This lack of standardization continues to be a hurdle (Kratz et al., 2019).

• Data governance is vital. Digitized patient slides contain sensitive information. Safe storage, access control, retention policies, and anonymization (if used for training) need to be in place.

• Workflow redesign is necessary. Decide if all slides should be scanned or just the flagged ones. Establish triggers for human review, manage image backlogs, and ensure quality checks of AI outputs.

• Staff training and acceptance are important. Moving from microscope to digital review requires training, managing change, monitoring performance, and collecting user feedback.

3.6 Summary

Slide digitization technologies have matured to the point where they are practical for clinical Haematology laboratories, especially for peripheral blood smear morphology. They provide the essential infrastructure that AI classification engines need. Success relies on more than just hardware; it also depends on strong smear preparation, calibration, redesigning workflows, integration with LIS, and data governance. Without these foundations, digital morphology may not perform well.

4. Clinical Applications

Here we look at how AI and digital morphology are used in real world Haematology labs. This includes peripheral blood smears, bone marrow aspirates and fluids, as well as the benefits, challenges, and specific case studies.

4.1 Routine Haematology laboratory use – peripheral blood smears

Most widespread use of digital morphology + AI in Haematology is in peripheral blood smear (PBS) review. Standard workflow: CBC + analyser flags → smear prepared → scanned/digitised → AI pre-classification of cells → technologist reviews flagged/abnormal cells + summary → report generated.

In Xing et al. (2023) the workflow of AI assisted morphology review led to improved accuracy (especially for abnormal cells) and reduced review time. Benefits reported: faster turnaround, lower human review burden, improved consistency, remote review capability. Additionally, in labs where staffing is constrained or volume is high, digital morphology enables more scalable review.

Benefits for teaching/academic labs are also significant: archived digital slides can serve for teaching technologists/residents, competency assessment, proficiency testing, and inter-laboratory consultation. The remote review capability is particularly relevant in regions with workforce limitations (e.g., many parts of India, including Assam) and for multi site networks.

4.2 Bone-marrow aspirate and body fluid morphology

In Xing et al. (2023), the workflow of AIassisted morphology review improved accuracy, especially for abnormal cells, and cut down review time. The reported benefits include faster turnaround, a lower burden on human reviewers, better consistency, and the option to review remotely. In labs with limited staff or heavy workloads, digital morphology offers a more scalable review process.

The advantages for teaching and academic labs are also noteworthy. Archived digital slides can be used to teach technologists and residents, assess competency, test proficiency, and facilitate consultations between laboratories. The ability to review remotely is especially crucial in areas with workforce challenges, such as many regions in India, including Assam, and for multisite networks.

4.3 Case studies and evidence

- **Xing et al. (2023):** AI-assisted manual leukocyte differentiation of 102 blood samples improved accuracy, sensitivity, specificity and reduced time.
- **Zhao et al. (2024):** Performance evaluation of Sysmex DI 60 in abnormal samples (n = 166) found strong correlation for neutrophils/lymphocytes/blasts but weaker for monocytes/plasma cells, and performance varied by WBC count category.
- **Kratz et al. (2019):** ICSH review of digital morphology analysers in Haematology: summarised multiple instruments, identified strengths/weaknesses and recommended standardisation.

4.4 Benefits

- Reduction in turnaround time (TAT) and technologist workload.
- Improved consistency and reduced inter observer variability.
- Remote review and consult capabilities expand access.
- Better archiving, teaching and training opportunities.
- Potential for integration with other digital data (CBC, flow cytometry, molecular) for richer diagnostic insights.

4.5 Challenges

- Slide and smear quality remain limiting factors—poor preparations reduce algorithm performance.
- Algorithm performance remains variable for rare events, dysplastic or overlapped cells, and extreme cell counts.
- Capital investment: slide scanners, storage, network infrastructure, software licensing and maintenance.
- Workflow change management: staff training, acceptance of digital review, managing image/scan backlog, defining human–AI responsibilities.
- Data management: storage, retrieval, backup, patient confidentiality, footprint of large image datasets.
- Validation in local context: many published studies are from high-resource settings; local labs may have different smear quality, staining protocols, workload patterns.
- Regulatory/ accreditation compliance: implementation must satisfy laboratory standards (see next section).

4.6 Implementation considerations for teaching/clinical labs (such as yours)

Given your role as clinical instructor and laboratory scientist in a teaching institution, here are some practical implementation suggestions:

- Establish robust slide preparation protocols (smear thickness, stain quality, metadata logging) before scanning.
- Determine scanning strategy: whether all slides or only flagged slides are digitised, to optimise resource use.
- Pilot the system: select a representative set of blood smears (normal, abnormal) and run parallel manual + digital/AI review; measure accuracy, review time, technologist satisfaction, discrepancy rate.
- Ensure human oversight: even with AI pre classification, expert review must remain for flagged or ambiguous cases (especially rare/abnormal morphology). The ICSH review emphasizes this.

- Use archived images for education/training: enable residents/technologists to review annotated digital slide banks, track their performance.
- Monitor key performance indicators (KPIs): TAT, number of slides needing manual review, error/ discrepancy rate, technologist time per slide, image backlog size, storage usage.
- Plan for staff training and change management: adopt digital review habits, ensure technologists are comfortable with digital interfaces, workflows.
- Align with accreditation needs: if your institution is undergoing NAAC or similar, digital morphology workflows and data management should be included in SOPs, quality control records, documentation.

4.7 Summary

The clinical adoption of AI-augmented digital morphology in Haematology laboratories is now a reality for peripheral blood smear review in many medium to large laboratories. The benefits are significant—but equally important are the practical implementation challenges and the fact that human expertise remains central, especially for complex morphologies and rare events. Teaching institutions have an opportunity both to adopt these workflows and to train the next generation of technologists and haematologists in digital morphology practice.

5. Validation and Regulatory Considerations

It would be irresponsible not to talk about the compliance, quality assurance and regulatory governance side of AI + digital morphology in Haematology. (Because yes, someone will audit this.)

5.1 Standards and Quality Control

The ICSH review (Kratz et ., 2019) remains a key reference: it emphasises that pre-analytic (slide prep, staining, smear quality), analytic (scanner calibration, image acquisition, algorithm performance) and post analytic (reporting, human review, archiving) parameters must be standardised for digital morphology analyser s.

Labs should perform method verification/validation: compare digital morphology + AI workflow with manual microscopy (the reference standard) in the local context (same smear prep, staining, patient population). Key metrics include accuracy, sensitivity, specificity, Kappa correlation with manual classification, turnaround time, and error or discrepancy rates. The real-world review by Kim et al. (2025) emphasizes that performance needs validation in the actual laboratory setting. Quality control (QC) must cover scanner focus/colour calibration, slide image quality audit (smear/stain quality), AI performance monitoring (e.g., number of flagged vs non-flagged cells, false negatives), and periodic review of algorithm outputs vs human review. External quality assessment (EQA) schemes specific to digital morphology remain under developed.

SOPs must cover slide scanning, image acquisition, review workflow, archiving, human verification of AI output, discrepancy resolution, version control of algorithms, data storage policy, and user training.

5.2 Regulatory Frameworks

Digital morphology systems and AI algorithms fall under evolving regulatory regimes (software as a medical device, decision support systems). Many commercial systems are cleared (e.g., in the US or EU) for use as “pre-classifiers,” with human review required. For example the Kim et al. (2025) review reports that as of October 2023 there were ~20 platforms commercially available and ~17 AI/ML devices cleared for peripheral blood smear analysis.

Laboratories must ensure compliance with national/local regulation (in India: e.g., Indian Council of Medical Research (ICMR), Central Drugs Standard Control Organization (CDSCO), and accreditation standards such as National

Accreditation Board for Testing and Calibration Laboratories (NABL)). Systems must be validated locally; algorithm "black box" issues, defined scope of use (sample types, WBC count ranges) and fall-back (manual review) must be clearly defined.

Risk management: The laboratory must define what happens when AI fails (poor smear quality, rare abnormal cells, extreme WBC counts). The human review pathways must be robust. Change management: when software/algorithm is upgraded, labs should re validate or re verify performance. Data governance: digitised patient slides = patient data; labs must implement appropriate security, access controls, retention policies, anonymisation (where relevant) and comply with data privacy regulations (e.g., India's Digital Data Protection).

Accreditation: For labs under ISO 15189, digital morphology workflows and AI must be included in the scope of accreditation, with evidence of validation, SOPs, QC records, training logs, image archiving policy, and periodic performance monitoring.

5.3 Practical Validation Workflow (Suggested)

For a laboratory using an AI enabled digital morphology system:

1. Define the scope: sample types (only PBS? bone marrow aspirate? body fluids?).

2. Prepare a test set: representative slides covering normal, abnormal, and flagged samples.

3. Run parallel manual reviews (microscopy) and digital/AI reviews. Record metrics: accuracy, sensitivity, specificity, Kappa, review time, and discrepancy rates.

4. Analyse results: identify sample types or morphological classes where AI does not perform well (for example, plasma cells, dysplastic forms, overlapping cells).

5. Establish review thresholds and human in the loop rules: for instance, all flagged slides plus a certain percentage of non flagged slides are reviewed by humans; manual review is mandatory for specific WBC ranges (for example, less than 1.5×10^9 or more than 30×10^9) as indicated in Zhao et al. (2024).

6. Document SOPs: scanning, classification/verification workflow, archiving, image retention, discrepancy management, and QC procedures.

7. Monitor performance continuously: keep logs of AI versus human discrepancies, turnaround times, backlog size, technologist time per day, storage usage, system uptime, and scanner focus/colour calibration checks.

8. Participate in EQA programs for digital morphology if available, or create internal benchmark slides for periodic reaudit.

9. Review and revalidate when major changes occur (algorithm upgrade, scanner hardware change, staining/protocol change).

10. Ensure training for technologists and haematologists: digital slide review, understanding AI outputs/flags, awareness of false negatives/positives, and recognition of algorithm limitations.

Validation Metric	**Description**	**Expected Standard**
Accuracy	% Correct classifications vs manual	≥90% for common cells
Sensitivity	Ability to detect abnormal cells	High (≥85%)
Specificity	Correctly identifying normal cells	≥90%
Kappa Agreement	Agreement with expert reviewers	≥0.75
Turnaround Time	Time from scan → report	Reduced vs manual
False-Negative Rate	Missed abnormal cells	As low as possible

WBC Count Performance	AI stability across ranges	Must verify all ranges

5.4 Summary

Validation and regulatory compliance are not optional addons they are central to the safe and effective adoption of AI + digital morphology in Haematology laboratories. Without robust validation, QC and human oversight frameworks, the risk of diagnostic error remains. Teaching institutions must emphasise these aspects in training technologists and residents.

6. Future Directions

Because yes, the future keeps coming. This section looks at new trends, possible innovations, and how AI and digital morphology might connect with personalized medicine in Haematology.

6.1 Advanced AI models and architectures

- **Foundation models for cell images.** The "DinoBloom" model (Koch et al., 2024) exemplifies a self supervised foundation model trained on >380,000 white blood cell images across domains; it showed improved generalisability across labs, stains and modalities. Similar models tailored to red cells, platelets, bone marrow aspirates may emerge.
- **Self-supervised, weakly supervised and anomaly-detection frameworks.** These will mitigate annotation bottlenecks. For instance, the WBC dataset (Tsutsui et al., 2023) provides detailed morphological attributes for 10,000 white blood cell images. This allows for explain ability and detailed feature models.
- **Multimodal integration.** Future systems may combine digital morphology images with CBC numeric output, flow cytometry, cytogenetics/molecular data, and clinical metadata to predict diagnosis, prognosis and therapy responses.
- **Explainable AI (XAI) and human–AI partnership.** As AI systems become more embedded, transparency ("why did the model classify this as a blast?") and uncertainty quantification will become essential for clinical trust and regulation.
- **Federated learning / decentralised data networks.** Given data privacy and heterogeneity across labs, future models may train across institutes in a federated fashion while preserving data privacy and local variation adaptation.

6.2 Laboratory ecosystem and personalised medicine

- **Hybrid** human and AI workflow. The nearterm model will likely keep human review of AIflagged cases, with AI doing preclassification instead of fully automated machine classification. The realworld review (Kim et al., 2025) expects this hybrid approach.
- **Tele Haematology and networked review.** In distributed geographies (including India, northeast region like Assam) digital morphology enables remote review by expert centres, pooling resources, improving equity of diagnostics.
- **Training and education.** Digital slide banks, AI annotated morphology, virtual microscopy modules will become common in technologist/hematologist training. You (as instructor) can leverage this to build curriculum modules.
- **Morphology to molecular phenotype prediction**. New research indicates that morphology characteristics might relate to genetic or molecular abnormalities, such as in AML and MDS. AI could connect morphology with molecular diagnostics. This connection may allow for earlier risk assessment or treatment recommendations.
- **Continuous learning and QC dashboards.** Digital morphology systems may incorporate feedback loops: tracking AI performance, drift (due to stain/slide change), error logging, automated QC dashboards for lab managers, technologists, pathologists.

- **Standardisation and global interoperability.** As the field matures we expect greater standardisation: image file formats (DICOM for pathology/morphology), staining/slide prep guidelines, external proficiency schemes for digital morphology, regulatory clarity for AI/ML in Haematology diagnostics.

6.3 Challenges and caveats

- Infrastructure and digital divide: Many labs, especially in resourceconstrained areas, may lack the scanner and IT infrastructure. Implementation must consider cost, maintenance, training, and sustainability.
- Ethical, legal, and data governance issues: AI decisions, data privacy especially for large archives of patient images algorithm transparency, and liability when AI makes mistakes are important topics.
- Human expertise remains essential: Despite progress in AI, human review of morphology is crucial for rare and complex cases, as well
- Business and return-on-investment models: While efficiency gains are possible, labs must quantify value (reduced labour cost, faster TAT, fewer repeat slides/errors) to justify investment; in teaching hospitals, training/education benefits are added value.
- Regulatory lag: Technology may outpace regulation; labs must ensure safe, validated deployment rather than early “beta” use in patient workflows without oversight.

6.4 Summary

The horizon for AI + digital morphology in Haematology is exciting: foundation models, multimodal diagnostics, federated learning, digital training platforms, and personalised medicine. However, the transition must be thoughtful, grounded in validation, human expertise and infrastructure readiness. Teaching laboratories like yours can lead the way by combining digital morphology adoption with education of the next generation of Haematology technologists/clinicians.

7. Conclusion

The integration of artificial intelligence and digital morphology is poised to transform Haematology laboratories. The evolution from manual microscopy to digitised, AI augmented workflows enables improvements in turnaround time, consistency, diagnostic accuracy and remote consultation capability. Current evidence supports the adoption of AI driven digital morphology particularly for peripheral blood smear review—in many laboratories. But critical challenges remain: slide and stain quality, rare/abnormal morphology classification, data annotation and domain shift, workflow redesign, infrastructure investment, regulatory compliance and staff training.

For a teaching clinical institution such as yours, success in implementation will require not just purchase of scanners and software, but attention to workflow redesign, robust validation in the local setting, hybrid human–AI review, staff training, archiving/teaching platforms and ongoing performance monitoring. The regulatory and quality assurance foundational work must not be neglected.

Looking forward, the next generation of digital morphology systems will incorporate foundation AI models, multimodal data synthesis, federated learning and deeper ties with personalised medicine but human expertise will continue to be central. Embracing this change now positions labs to lead in the era of digital Haematology.

In short: the future of Haematology laboratories is digital, networked, intelligent and human augmented.

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