International Journal of Innovative Research in Medical Science (IJIRMS)
Volume 11, Issue 01, January 2026,
https://doi.org/10.23958/ijirms/vol11-i01/2158

Original Article

Performance Evaluation of Artificial Intelligence-Driven Peripheral Blood Smear Interpretation

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Received: 27 December 2025; Accepted: 16 January 2026; Published: 20 January 2026

Abstract

Background: Peripheral blood smear (PBS) examination remains essential in hematological evaluation, providing morphological and diagnostic insight that cannot be fully substituted by automated cell counters. However, manual microscopy is labour-intensive and subject to inter-observer variability. Artificial intelligence (AI)-assisted digital microscopy systems, such as AI100 with Shonit™, aim to enhance reporting efficiency and consistency. ***Objective:*** To evaluate the diagnostic performance of AI100 with Shonit™ in comparison with manual microscopy for peripheral blood smear interpretation, focusing on leukocyte differential counts, detection of immature granulocytes and atypical/blast cells, and RBC and platelet morphology assessment. ***Methods:*** This cross-sectional study was conducted over ten months at the All India Institute of Medical Sciences, Gorakhpur. A total of 837 peripheral blood smears after exclusion of suboptimal slides were included in the study. Manual microscopy served as the reference standard. The same smears were analysed using AI100 with Shonit™, and results were compared. Pearson correlation, confusion matrix-based diagnostic accuracy, and morphology concordance percentages were calculated. ***Results:*** Fair correlations were observed for lymphocytes ($r = 0.773$, $r^2 = 0.597$), eosinophils ($r = 0.707$, $r^2 = 0.500$), and neutrophils ($r = 0.698$, $r^2 = 0.487$), while monocytes showed weaker correlation ($r = 0.272$, $r^2 = 0.074$). Immature granulocyte detection demonstrated sensitivity 81.8% and specificity 75.7%. Atypical/blast detection showed sensitivity 100% and specificity 69.6%. RBC morphology concordance ranged from high (ovalocytes 98.6%, tear drops 95.8%) to moderate (microcytes 56.3%). Platelet adequacy concordance was 66.9%. ***Conclusion:*** AI100 with Shonit™ shows strong performance for detection of atypical cells / blasts and Immature Granulocytes, supporting its role as a screening and workload-reduction tool. However, manual confirmation remains essential, particularly for ambiguous morphological abnormalities and platelet assessment. A hybrid AI-assisted workflow provides the most reliable clinical implementation.

Keywords: ***Sigtuple AI100; automation in hematology; AI-assisted peripheral blood smear; Automated analyzer; Image based analysis in peripheral blood smears.***

Introduction

Peripheral blood smear (PBS) examination remains a foundational component of hematological assessment, enabling morphological evaluation of erythrocytes, leukocytes, and platelets [1]. Unlike automated hematology analyzers, which provide quantitative data, PBS offers qualitative insights into cell structure, maturity, distribution, and pathological variants essential to diagnosing a spectrum of conditions including nutritional anemias, marrow failure syndromes, leukemias, myeloproliferative disorders, hemolytic states, and infectious disease-associated hematologic abnormalities [2].

Despite technological advancements in automated differential counting, manual microscopy remains indispensable when morphological abnormalities are suspected or when analyzer-generated flags indicate atypical cell populations [3]. However, manual review demands considerable expertise, is time-consuming, and demonstrates inter-observer variability influenced by training level, visual fatigue, and workload constraints [4]. Increasing diagnostic demands and limited availability of experienced haematology personnel globally have intensified the need for scalable, reproducible, and high-throughput smear evaluation strategies [5,6].

Recent developments in digital haematology integrate automated slide scanning with artificial intelligence (AI)-driven image classification. Deep learning-based models trained on large repositories of annotated cell images can segment, classify, and pre-flag abnormalities with high precision [7,8]. AI100 with Shonit™ is one such system designed to identify leukocyte subtypes, assess RBC morphological abnormalities, and evaluate platelet distribution patterns. Earlier studies have reported promising correlations between AI-generated differential counts and manual microscopy, though variability persists particularly in monocyte recognition and subtle RBC morphological variations [9-11].

However, the diagnostic performance of such systems must be validated across diverse clinical populations before routine implementation, particularly in tertiary care settings managing complex hematologic disorders. Therefore, the present study

evaluates AI100 with Shonit™ against manual microscopy for differential leukocyte counts, detection of immature granulocytes and atypical/blast cells, and assessment of RBC and platelet morphology.

Materials and Methods

This cross-sectional diagnostic comparison study was conducted in the Department of Pathology and Laboratory Medicine over a period of ten months. A total of 864 EDTA-anticoagulated peripheral blood samples submitted for routine hematological evaluation were initially included. 27 samples were excluded due to suboptimal smear preparation, excessive staining artifacts, or absence of a suitable monolayer region. Hence, 837 peripheral blood smears were finalized for evaluation and comparative analysis.

Peripheral blood smears were prepared using the standard wedge-spread technique to obtain a smooth film with a clearly defined monolayer and feathered edge. Slides were air-dried, fixed, and stained using Wright-Giemsa stain in accordance with institutional laboratory protocols. The slide was scanned on AI100 with Shonit™ system, a digital peripheral smear analysis and reporting system based on convolutional neural network. The same slide was also analysed via manual microscopy. The findings were compared to evaluate the diagnostic performance of AI100 with Shonit™ in comparison with manual microscopy for peripheral blood smear interpretation.

Statistical Analysis

Statistical analysis was performed to assess the performance of AI100 with Shonit™ using manual microscopy as the reference standard. Pearson correlation coefficients (r) and coefficients of determination (r^2) were calculated to assess linear association between manual and AI100 with Shonit™ differential counts for neutrophils, lymphocytes, monocytes, and eosinophils.

For RBC morphology, semiquantitative manual grading was standardized by grouping Nil and + as Negative, and ++ and +++ as Positive, converting each RBC parameter into a binary classification for comparison. A 2×2 confusion matrix was generated for each RBC morphological feature to derive true positives, true negatives, false positives, and false negatives. From this, concordance percentage, sensitivity, specificity, and overall agreement were calculated relative to manual microscopy.

For immature granulocytes (IG) and atypical/blast detection, a threshold of ≥5 cells per 100 leukocytes was used to classify cases as positive. Binary outcomes were compared using 2×2 contingency matrices to compute sensitivity, specificity, diagnostic accuracy, precision, and Cohen's kappa coefficient.

Platelet adequacy comparison required alignment of differing classification scales. Manual platelet adequacy was categorized into three groups (thrombocytopenia, adequate, thrombocytosis), while the AI system assigned four platelet adequacy levels. Therefore, a 3×4 comparison matrix was constructed and concordance calculated based on exact or clinically proximal category agreement. Platelet clumping and giant platelets were evaluated as binary variables and compared using 2×2 agreement analysis.

All statistical calculations were performed using Microsoft Excel and IBM SPSS. A p-value < 0.05 was considered statistically significant.

Results

The comparison results of a total of 837 samples are shown below using statistical techniques and scatter plots:

Table1: Morphology concordance of AI 100 in comparison to manual microscopy for RBCs, platelets

Cell categories	Parameter	Concordance (%)
RBC anisocytosis	Microcytes	56.3
RBC anisocytosis	Normocytes	59.6
RBC anisocytosis	Macrocytes	77.2
RBC poikilocytosis	Ovalocytes	98.6
RBC poikilocytosis	Elliptocytes	99.9
RBC poikilocytosis	Target Cells	82.8
RBC poikilocytosis	Tear Drop Cells	95.8
RBC poikilocytosis	Fragmented Cells	52.3
nRBC	nRBC	97.1
Platelets	Platelet Adequacy	66.9
Platelets	Platelet Clumps	38.9
Platelets	Giant Platelets	16.6

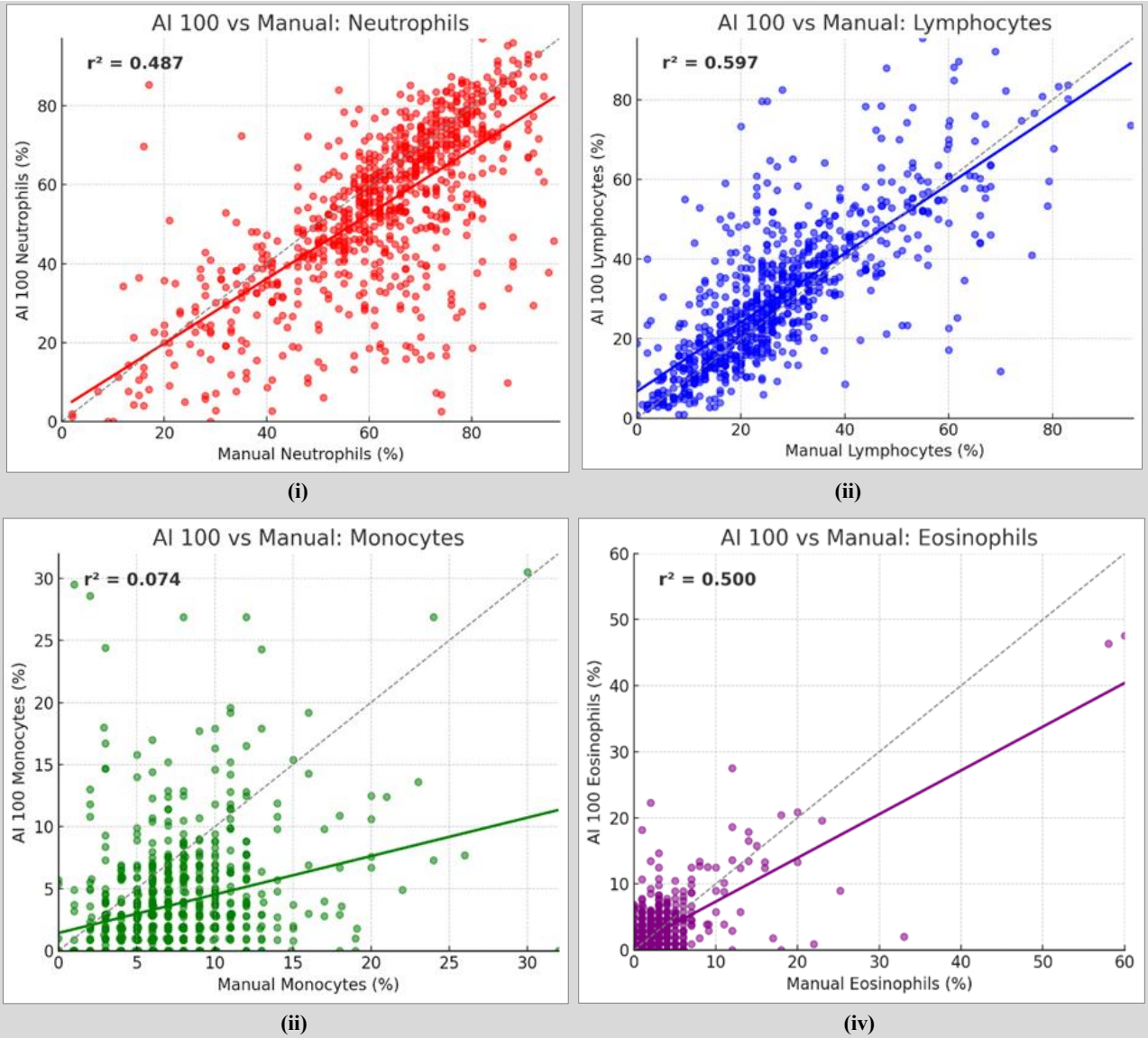

Figure1 (i-iv): The Pearson correlation (r) of neutrophils, lymphocytes, monocytes and eosinophils between AI 100 and manual microscopy for WBC percentage was 0.698, 0.773, 0.272 and 0.707 respectively.

Table 2 highlights the diagnostic performance (sensitivity and specificity) of AI 100 in detecting IGs and atypical/blast cells in overall agreement with manual microscopy.

Cell Type	True Positive	False Positive	True Negative	False Negative	Sensitivity	Specificity	Overall Agreement
Immature Granulocytes (IGs)	9	201	625	2	81.8%	75.7%	75.7%
Atypical/Blast cells	6	252	578	0	100.0%	69.6%	69.9%

Discussion

The AI100 with Shonit™ system demonstrated fair correlation with manual microscopy for common leukocyte classes and high sensitivity for detecting clinically relevant abnormal cell populations such as immature granulocytes and atypical/blast forms. These findings align with prior investigations showing that AI-based digital morphology systems enhance efficiency and reproducibility in hematology laboratories [9,10].

However, challenges persist in monocyte classification due to overlapping morphologies, particularly in inflammatory and dysplastic states. Similar limitations have been noted across digital morphology platforms [12-14]. RBC morphology detection was reliable for distinctive shapes (e.g., ovalocytes, tear drops) but less consistent for subtle anisocytosis–likely reflecting the complexity of gradient-based morphology recognition.

Platelet morphology interpretation remains the weakest domain due to technical factors including platelet size overlap, staining variability, and tendency for clumping artifacts.

Considering the Clinical Implication of AI100 with Shonit™, it can be used in a hybrid model – AI performs screening and pre-classification, while haematologists review flagged abnormalities. This approach increases throughput without compromising diagnostic accuracy.

Conclusion

AI100 with Shonit™ is a valuable adjunct to manual smear examination, offering efficiency and consistency benefits. Manual review remains essential in ambiguous cases. Integration of AI into routine hematology workflows is feasible and advantageous when applied with expert oversight.

Abbreviations

AI: Artificial Intelligence
PBS: Peripheral Blood Smear
IGs: Immature Granulocytes

Declarations

Ethical Approval and consent to participate

The authors assert that all procedures contributing to this study was performed in accordance with the ethical standards as laid down in the 1964 Declaration of Helsinki and its later amendments or comparable ethical standards.

Availability of supporting data

Data supporting the findings of this study are available from the corresponding author on request.

Sources of Funding

This research did not receive a specific grant from any funding agency, commercial or not-for-profit sector.

Conflicts of Interest

None

Author contribution

All the authors contributed to the study conception and design and data analysis. All the authors read and approved the final manuscript.

Competing Interests

The author(s) declare none to disclose

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