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APPLICATION OF ARTIFICIAL INTELLIGENCE IN WHITE BLOOD CELL CLASSIFICATION BASED ON MICROSCOPIC IMAGES: A SCOPING REVIEW

Annisa Nur Hasanah[1], Oktafirani Al Sas[2], Yosua Darmadi Kosen[3]

[1]Medical Laboratory Technology, Health Faculty, Bakti Tunas Husada University, Tasikmalaya,Indonesia
[2]Medical Laboratory Technology, An Nashr Health Analyst Academy, Cirebon, Indonesia
[3]Faculty of Medicine, Maranatha Christian University, Bandung, Indonesia

ABSTRACT

White blood cell (WBC) classification plays a crucial role in hematological diagnosis and is typically performed manually using microscopic images. However, manual analysis is limited by subjectivity and time inefficiency. With recent technological advances, artificial intelligence (AI) offers promising solutions for automated WBC classification that enhance accuracy and efficiency. This study presents a scoping review of 20 scientific publications discussing AI applications in microscopic image-based WBC classification. Literature searches were conducted in PubMed, ScienceDirect, Institute of Electrical and Electronics Enginers (IEEE) Xplore, and Google Scholar using relevant keywords such as “AI”, “white blood cell”, and “microscopic image”. Findings indicate that the most commonly used method is Convolutional Neural Network (CNN), either standalone or hybrid (e.g., YOLOv5, ResNet, Vision Transformer), achieving accuracies up to 99.7%. The datasets were mostly public Blood Cell Count and Detection (BCCD), Leucocyte Images for Segmentation and Classification (LISC), Raabin-WBC or local laboratory sources. The reviewed studies aimed at automatic WBC detection, classification, and morphological identification. Despite encouraging outcomes, challenges such as external validation and limited access to real clinical data remain. Overall, AI has proven effective in enhancing speed, accuracy, and objectivity in WBC classification. Further research is needed to support AI integration into real-world clinical laboratory practice.

Keywords : Artificial intelligence, White blood cells, Classification, Microscopic image, CNN

Correspondence:
Annisa Nur Hasanah
Medical Laboratory Technology, Health Faculty, Bakti Tunas Husada University
Jalan Letjen Mashudi No. 20, Kota Tasikmalaya, Jawa Barat
annisanur@universitas-bth.ac.id

INTRODUCTION

White blood cells (leukocytes) play a crucial role in the immune system by combating infections and maintaining immunological balance within the body. Examination of leukocyte morphology through peripheral blood smears remains one of the primary diagnostic methods for various hematological disorders, including systemic infections, leukemia, and autoimmune diseases (Bain, 2015). However, manual classification of white blood cells is inherently subjective, requires expert interpretation, and is prone to inter-observer variability (Rezatofighi, 2011).

Recent advancements in artificial intelligence (AI), particularly in machine learning and deep learning, offer promising solutions for enhancing the speed and accuracy of leukocyte classification based on microscopic images. Convolutional Neural Network (CNN) models have been widely utilized in medical image processing and have demonstrated efficacy in recognizing morphological patterns of leukocytes (Liang, 2018; Mohamed, 2021) The integration of AI not only reduces the workload of laboratory analysts but also enhances the objectivity and reproducibility of diagnostic results. In response to the increasing demand for rapid and accurate hematological diagnosis, information technology is becoming increasingly vital in supporting clinical laboratory workflows. One emerging approach is the use of AI for the automated detection and classification of white blood cells from microscopic images. This method is particularly relevant given the growing workload of laboratory personnel and the need for more objective and efficient analysis (Abou Ali, 2023).

With the rapid evolution of deep learning algorithms, several studies have investigated the effectiveness of models such as Convolutional Neural Networks (CNN), You Only Look Once version 5 (YOLOv5) and Vision Transformers in analyzing leukocyte morphology. Findings from these studies suggest that AI-driven approaches can significantly improve classification accuracy while minimizing reliance on individual expertise, thereby reducing the risk of misinterpretation. These innovations highlight the potential of AI to serve as a critical tool in diagnostic procedures, especially in regions with limited access to hematology experts (Chen, 2024).

Nevertheless, the implementation of AI in hematology faces several challenges, including the lack of standardized datasets, limited availability of diverse clinical data, and the need for broader model validation. Consequently, a comprehensive and systematic literature review is essential to understand the evolution of this technology, identify existing challenges, and outline future research directions. This review aims to provide a thorough mapping of AI applications in leukocyte classification using microscopic imagery (Jung, 2019).

As the body of research in this field continues to grow, there is a pressing need for a systematic mapping of the literature to identify developments, emerging trends, and challenges in the use of AI for white blood cell classification. Accordingly, this study aims to conduct a scoping review of scientific publications that explore the application of artificial intelligence in microscopic image-based leukocyte classification. The findings of this review are expected to inform future research efforts and reinforce the integration of AI technology in hematological diagnostics.

METHOD

This study is a scoping review aimed at systematically identifying, summarizing, and evaluating various applications of artificial intelligence (AI) in the classification of white blood cells based on microscopic image data. The scoping review approach was chosen to map the existing scientific literature, identify research gaps, and summarize the AI methods and technologies used in white blood cell classification.

The research methodology follows the scoping review framework developed by (Arksey, 2005). The review process consists of five interrelated stages. The first stage involves identifying the research questions that form the foundation for the systematic exploration of relevant literature. In the second stage, relevant studies are identified through systematic searches across multiple scientific databases using predefined keywords and eligibility criteria.

The third stage is the selection of studies, beginning with title and abstract screening to determine initial relevance, followed by full-text review to confirm eligibility based on inclusion and exclusion criteria. The inclusion criteria comprise scientific articles written in English or Indonesian to ensure accessibility for the reviewers. Only primary studies employing experimental or observational designs are included, as these provide empirical data directly supporting the analysis. Furthermore, eligible studies must specifically use microscopic images for the classification of white blood cells and incorporate AI technologies such as Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Random Forest, or other deep learning methods.

Exclusion criteria include articles in the form of reviews, opinion papers, editorials, or abstracts without full-text availability, as these lack sufficient methodological and result-based information for analysis. Studies that do not use microscopic images as primary data are also excluded, as they fall outside the scope of this research. Additionally, studies that rely solely on manual classification methods without the use of AI are not considered, as they do not align with the study's primary objective of exploring AI applications in image-based leukocyte classification.

The next stage involves data extraction and presentation, which includes collecting key information from each selected study, such as the type of AI method used, data sources, dataset size, and main outcomes achieved. Finally, the results are reported through analysis of the key findings and a thematic mapping of the reviewed studies, providing a comprehensive overview of trends, strengths, and research gaps in the application of AI for the classification of white blood cells based on microscopic images.

The literature search was conducted across scientific databases such as PubMed, ScienceDirect, IEEE Xplore, and Google Scholar, covering publications from 2013 to 2024. The search keywords included: “Artificial Intelligence,” “White blood cell classification,” “Microscopic image,” “Deep learning,” “Machine learning,” and “Hematology AI”. The extracted data included the following items; (1) Author(s) and year of publication; (2) Type of AI method applied; (3) Source and size of the dataset; (4) Objectives and main outcomes (e.g., accuracy, sensitivity, et; (5) Strengths and limitations of the applied methods

RESULT

Based on the analysis of 20 articles that met the inclusion criteria, it was found that the application of artificial intelligence in white blood cell (WBC) classification continues to undergo significant advancement, in terms of the methods employed, the types of microscopic data analyzed, and the accuracy of the resulting models. Most studies utilized Convolutional Neural Network (CNN) approaches, either purely or in hybrid forms combined with other models such as YOLOv5, Vision Transformer (ViT), and even traditional classification methods like Support Vector Machine (SVM) and Random Forest (RF). This highlights the dominance of deep learning approaches in WBC detection and classification.

Table 1: Data Extraction - Scoping Review In White Blood Cell Classification

No	Writer & Year	Title	Method AI	Source of Microscope Data	Data Size	Aims	Accuracy
1	Rehman et al., 2020	*Classification of white blood cells using deep features learning*	CNN (Deep Learning)	LISC Dataset (open-source)	2.000 pics	Automatic Detection WBC	94,5%

2	Baydilli et al., 2021	*White blood cell classification using SVM in microscopic images*	SVM	Local microscopic	500 pics	5 types classification WBC	88,7%
3	Mohamed et al., 2022	*A hybrid random forest model for white blood cell classification*	Random Forest	Private dataset (Egypt)	1.200 pics	Segmentation and classification WBC	91%
4	Harouni et al., 2021	*Automatic leukocyte detection using deep transfer learning*	Transfer Learning (ResNet50)	BCCD Dataset (public)	3.100 pics	Automatic Identification	96,2%
5	Lu et al., 2023	*A real-time WBC detection system using YOLOv5 and hybrid CNN*	YOLOv5 + CNN Hybrid	Citra digital China hospitals	4.500 pics	Automatic Realtime detection WBC	(98%)
6	Chen et al., 2024	*DAFFNet: A Dual Attention Feature Fusion Network for Classification of White Blood Cells*	CNN (DAFFNet)	PBC, LISC, Raabin-WBC, BCCD, LDWBC, Labelled	Undetected	Classification WBC with morphology and semantics	91.3%–99.71%
7	Aksoy, 2024	*An Innovative Hybrid Model for Automatic Detection of White Blood Cells in Clinical Laboratories*	MobileNetV2 + EfficientNetB0	Mixed datasets	Undetected	Automatic detection WBC in Lab	95.6%
8	Jung et al., 2019	*W-Net: A CNN-based Architecture for White Blood Cells Image Classification*	CNN (W-Net)	Dataset from The Catholic University of Korea	6.562 pics	Classficiation 5 types WBC	97%
9	Shu et al., 2020	*Artificial Intelligence Enabled Reagent-free Imaging Hematology Analyzer*	CNN	Undetected	Undetected	Leucocytes classification without reagen	Undetected
10	Xu et al., 2021	*TE-YOLOF: Tiny and Efficient YOLOF for Blood Cell Detection*	YOLOF (One-stage detector)	Undetected	Undetected	Detection cell in microscopes	Undetected
11	Unwritten, 2022	*White Blood Cell Classification Using Texture and RGB Features of Oversampled Microscopic Images*	Tidak disebutkan	Undetected	Undetected	WBC Classification with Texture fiture and RGB	Undetected

12	Unwritten, 2023	*Artificial Intelligence of Digital Morphology Analyzers Improves the Efficiency of Manual Leukocyte Differentiation of Peripheral Blood*	AI (Undetected)	Undetected	Undetected	Increasing manually efficiency classification leukocytes	Undetected
13	Unwritten, 2024	*Deep Learning-Based Image Annotation for Leukocyte Segmentation and Classification of Blood Cell Morphology*	Deep Learning (Undetected)	Undetected	Undetected	Segmentation and classification WBC	Undetected
14	Unwritten, 2020	*Artificial Intelligence and Digital Microscopy Applications in Diagnostic Hematopathology*	AI (Undetected)	Undetected	Undetected	Application AI in hematopatology diagnostic	Undetected
15	Unwritten, 2022	*A Review on Machine Learning-Based WBCs Analysis in Blood Smear Images: Key Challenges, Datasets, and Future Directions*	Review (ML variety method)	Undetected	Undetected	WBC analysis review based ML	Undetected
16	Abou Ali et al., 2023	*White Blood Cell Classification: Convolutional Neural Network (CNN) and Vision Transformer (ViT) under Medical Microscope*	CNN and Vision Transformer	Undetected	Undetected	Compared CNN and ViT in WBC Classification	Undetected
17	Manthouri et al., 2022	*Computational Intelligence Method for Detection of White Blood Cells Using Hybrid of Convolutional Deep Learning and SIFT*	CNN + SIFT	Undetected	Undetected	WBC Detection combination CNN amd SIFT	Undetected
18	Unwritten, 2023	*Automated Blood Cell Detection and Classification in Microscopic Images Using YOLOv11 and Optimized Weights*	YOLOv11	Undetected	Undetected	Automatic detection and classification cell	Undetected

19	Shahin et al., 2019	*White Blood Cells Identification System Based on Convolutional Deep Neural Learning Networks*	CNN	Undetected	Undetected	Identification WBC using CNN	Undetected
20	Yu et al., 2017	*Automatic Classification of Leukocytes Using Deep Neural Network*	Deep Neural Network (DNN)	Undetected	Undetected	Automatic classification cell	Undetected

DISCUSSION

Recent advancements in deep learning have significantly influenced white blood cell (WBC) classification using microscopic images. Among the various methods, Convolutional Neural Networks (CNN) emerged as the most dominant approach, used either independently or in combination with other models. Hybrid strategies—such as CNN with YOLOv5 or Vision Transformers—demonstrated strong performance in terms of both detection speed and classification accuracy. For instance, the study by (Lu, 2023). Employed a hybrid YOLOv5-CNN model to support real-time detection, while (Chen, 2024) implemented the DAFFNet architecture, which integrates semantic and morphological features to achieve accuracies up to 99.71%.

Although traditional machine learning models such as Support Vector Machine (SVM) and Random Forest are still in use, their performance generally falls short when compared to deep learning methods. For example, (Baydilli, 2021) reported 88.7% accuracy using SVM, whereas (Mohamed, 2021) achieved 91% using Random Forest. These conventional methods may still be applicable in scenarios with limited computational resources or in settings that require more interpretable models.

The source and quality of image datasets play a crucial role in model performance. Most studies utilized public datasets such as BCCD, LISC, Raabin-WBC, and PBC, which are widely accessible and include labeled WBC images. However, several studies did not report dataset size, data origin, or labeling standards, making cross-study comparison and replication difficult.

Studies that incorporated large and diverse datasets generally showed better model generalization and performance. For example, datasets containing more than 3,000 images (Jung, 2019; Lu, 2023) often yielded models with higher accuracy and better morphological differentiation. Despite this, real-world clinical datasets remain underutilized, and only a few studies referenced images sourced directly from hospital laboratories.

The reviewed studies highlight that accuracy is influenced by several technical factors, including model architecture, feature fusion strategies, dataset size, and data diversity. Techniques that combine low-level morphological features with high level semantic representations tend to yield better results. Attention-based models, like DAFFNet (Chen, 2024) demonstrate that incorporating semantic context enhances cell differentiation capability.

Moreover, image preprocessing and augmentation methods although not consistently reported are essential for improving model robustness and preventing overfitting. The lack of standardization in these steps contributes to variability in reported outcomes across studies. Only a subset of studies conducted comparative evaluations across multiple architectures, limiting the understanding of which approaches are truly optimal.

Despite the promising results, several challenges hinder the practical implementation of AI in hematological diagnostics. First, external validation is rarely conducted, raising concerns about the generalizability of models across different laboratory settings and patient populations. Many models are tested only on the datasets they were trained on, which may lead to overfitting and biased results.

Second, the limited use of real clinical data and underrepresentation of diverse ethnic and demographic groups reduces the reliability of AI models in global clinical contexts. To address this, future studies must prioritize the inclusion of diverse, well-annotated datasets and conduct multicenter validations.

Finally, interpretability and user integration remain critical issues. For AI tools to be adopted in routine laboratory workflows, they must be accompanied by intuitive user interfaces, proper training for healthcare personnel, and compliance with regulatory standards. Collaboration between researchers, clinicians, and AI developers is essential to bridge the gap between laboratory research and clinical application.

CONCLUSION

This scoping review has synthesized findings from 20 scientific studies on the application of Artificial Intelligence (AI) in the classification of white blood cells (WBCs) based on microscopic images. The evidence demonstrates that deep learning models, particularly Convolutional Neural Networks (CNN) and their hybrid variants, are the most commonly employed and effective techniques for enhancing classification accuracy and diagnostic efficiency. AI approaches have shown the ability to improve objectivity, reproducibility, and processing speed in hematological image analysis. Models that integrate semantic and morphological features, supported by well structured datasets, have achieved classification accuracies exceeding 99%. Nonetheless, despite the technological progress, significant challenges remain especially in terms of external validation, dataset standardization, and real-world clinical integration. In conclusion, AI holds strong potential to support and augment hematological diagnostics. However, its transition from research to clinical routine use requires strategic efforts focused on generalizability, interpretability, and regulatory compliance.

RECOMMENDATION

Based on the findings of this review, several recommendations can be proposed for the future development and implementation of artificial intelligence in white blood cell classification. First, there is a need for the development and standardization of larger, more diverse, and representative microscopic image datasets from various populations to enhance the validity and generalizability of AI models. Second, greater attention should be given to the external validation of AI models. Many current studies are limited to internal validation, making it difficult to ascertain the effectiveness of the models when applied to data from other hospitals or laboratories. Third, to encourage the widespread adoption of AI technology in clinical laboratories, it is essential to develop user-friendly system interfaces and provide training for healthcare professionals on the use and interpretation of AI-based systems.

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