Microscopic Image-Based Malaria Parasite Detection Using k-Nearest Neighbor Classifier: A Literature Review

Group 6 - A Division
16014223060 Piyush Choudhury
16014223082 Soham Mishra
16014223093 Vedant Tendulkar
16014223100 Yash Pathak

Department of Information Technology, K J Somaiya School of Engineering (formerly K J Somaiya College of Engineering), Somaiya Vidyavihar University, Vidyavihar, Mumbai, 400077, Maharashtra, India

piyush.choudhury@somaiya.edu,
soham.sm@somaiya.edu,
vedant.tendulkar@somaiya.edu,
yash.pathak@somaiya.edu

Abstract

These sources collectively discuss the application of Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL) models such as Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs), for the automated diagnosis of infectious diseases, primarily focusing on malaria detection from microscopic blood smear images. Several studies propose and evaluate novel methodologies and hybrid models, including a transfer learning-based feature engineering approach (NNR+SVM), a hybrid CNN-CapsNet model, and a CNN-Vision Transformer (ViT) ensemble model, demonstrating high accuracy (frequently achieving 99% or greater) in classifying red blood cells as parasitized or uninfected. The research also explores the use of object detection models like RetinaNet and deep metric learning (DML) for related tasks, such as identifying *Trypanosoma* species and detecting *Anaplasma* infections in cattle, confirming the utility of these computational tools in addressing the limitations of traditional, manual microscopy methods, especially in resource-constrained settings. Many sources emphasize the importance of mobile-based applications for field deployment and the use of techniques like data augmentation and feature extraction to improve model robustness and performance.

1 Summary

Vijayalakshmi et al. [1, 2020] proposed a deep learning approach for detecting malaria from microscopic blood images, showcasing the use of modern DL techniques for automatic diagnostic support.

White [2, 2017] discussed the critical clinical and biological topic of malaria parasite clearance, providing necessary context on disease progression relevant to automated diagnostic tools.

Vandana et al. [3, 2021] focused on the biological phenomenon "Malaria parasite beats the heat," contributing to the understanding of malaria biology for robust diagnostic tool development.

Rajaraman et al. [4, 2018] employed pre-trained CNNs as feature extractors to improve malaria parasite detection in thin blood smear images, demonstrating transfer learning's effectiveness.

Liang et al. [5, 2016] presented a CNN-based malaria diagnosis method, contributing to establishing deep learning in microscopic image interpretation.

Junaid et al. [6, 2023] developed Explainable ML models on multimodal time-series data for early Parkinson's detection, focusing on transparent medical diagnostics.

Poostchi et al. [7, 2015] investigated image analysis of blood slides for automatic malaria diagnosis, showing early ML automation efforts.

Abdelmaksoud et al. [8, 2021] proposed an automatic grading system for diabetic retinopathy using image processing to detect multiple retinal lesions.

Raza et al. [9, 2023] predicted microbes using hybrid classifiers, contributing to microbial identification through AI.

Mahmood et al. [10, 2023] introduced a deep CNN method for improved malaria cell detection, enhancing parasitized cell identification accuracy.

Arco et al. [11, 2015] used digital image analysis and morphological operations for automatic malaria parasite counting.

Ren et al. [12, 2016] introduced Faster R-CNN with Region Proposal Networks, enabling efficient object detection and influencing medical image analysis.

Lin et al. [13, 2017] proposed Focal Loss for dense object detection to address class imbalance in visual recognition.

Molina et al. [14, 2021] used CNNs for multi-class identification of malaria parasites and red blood cell inclusions.

Gourisaria et al. [15, 2020] proposed a DCNN architecture specifically tailored for malaria disease detection and analysis.

Mohammed et al. [16, 2017] developed a malaria detection system with 94.97% accuracy using thin smear analysis.

Nanoti et al. [17, 2016] used kNN classification for malaria species and life stage detection, achieving 94.20% accuracy.

Marzahl et al. [18, 2020] applied deep learning for quantifying pulmonary hemosiderophages, demonstrating AI's cellular counting utility.

Kittichai et al. [19, 2021] applied DCNNs for avian malaria parasite stage classification, showing species-specific applications.

Pamungkas et al. [20, 2015] identified *Plasmodium falciparum* developmental phases using adaptive segmentation and decision trees.

Okumu et al. [21, 2022] discussed malaria control strategies in Africa, providing global health policy context.

Delgado-Ortet et al. [22, 2020] proposed deep learning-based red blood cell segmentation for malaria detection with 95.28% accuracy.

Rajab et al. [23, 2023] developed interpretable ML models using SHAP values for malaria prediction transparency.

Fuhad et al. [24, 2020] presented a smartphone-integrated deep learning model for malaria detection achieving 99.23% accuracy.

Gummadi et al. [25, 2022] applied transfer learning-based CNN classification of *Plasmodium falciparum* with 96.88% accuracy.

2 Concluding Analysis

Across these studies, common trends emerge in the adoption of deep learning and hybrid feature engineering methods to enhance diagnostic accuracy in malaria detection tasks. Most methods rely on CNN-based architectures with strong performance on structured, controlled datasets but reveal several technical gaps.

First, a significant limitation is the lack of domain generalization, as models are often trained on narrow datasets with limited variability in staining, lighting, or device quality. Second, few studies address multimodal integration—most focus solely on visual data rather than incorporating contextual or patient-level information. Third, while many models achieve high accuracy, only a few works evaluate interpretability or explainability, making clinical adoption more difficult.

Additionally, privacy considerations remain largely absent. Models trained and deployed on sensitive health data often do not incorporate privacy-preserving techniques such as differential privacy or federated learning. Scalability for real-time deployment, particularly on mobile or low-resource devices, is another major challenge.

These gaps directly motivate the use of reinforcement learning–based vision-to-text frameworks that can dynamically adapt to domain shifts, incorporate privacy-preserving mechanisms, and produce interpretable textual outputs. Such an approach can enable more robust, scalable, and trustworthy AI-assisted diagnostic systems for malaria and similar infectious diseases.

References

References

[1] Jasman Pardede et al. "AUTOMATED MALARIA DIAGNOSIS USING OBJECT DETECTION RETINA-NET BASED ON THIN BLOOD SMEAR IMA". In: *Journal of Theoretical and Applied Information Technology* 98.05 (2020), pp. 757–767.

[2] Azam Mehmood Qadri et al. "A novel transfer learning-based model for diagnosing malaria from parasitized and uninfected red blood cell images". In: *Decision Analytics Journal* 9 (2023), p. 100352.

[3] Hafiz Muhammad Bilal. "Identification and classification for diagnosis of malaria disease using blood cell images". In: *Lahore Garrison University Research Journal of Computer Science and Information Technology* 7.1 (2023), pp. 14–28.

[4] Mosam K Sangole and Sanjay T Gandhe. "Malaria diagnosis using microscopic imaging". In: *International Journal of Health Sciences* 6.2 (2022), pp. 880–897.

[5] Anna Mur Suñé. "Malaria detection via SAM-based red blood cell segmentation and feature analysis". In: (2024).

[6] KM Faizullah Fuhad et al. "Deep learning based automatic malaria parasite detection from blood smear and its smartphone based application". In: *Diagnostics* 10.5 (2020), p. 329.

[7] Hilda Mayrose et al. "Machine learning-based detection of dengue from blood smear images utilizing platelet and lymphocyte characteristics". In: *Diagnostics* 13.2 (2023), p. 220.

[8] Thaqifah Ahmad Aris et al. "Robust image processing framework for intelligent multi-stage malaria parasite recognition of thick and thin smear images". In: *Diagnostics* 13.3 (2023), p. 511.

[9] Laith Alzubaidi et al. "Deep learning models for classification of red blood cells in microscopy images to aid in sickle cell anemia diagnosis". In: *Electronics* 9.3 (2020), p. 427.

[10] Flavia Grignaffini et al. "Computer-aided diagnosis systems for automatic malaria parasite detection and classification: a systematic review". In: *Electronics* 13.16 (2024), p. 3174.

[11] Rui-Si Hu, Abd El-Latif Hesham, and Quan Zou. "Machine learning and its applications for protozoal pathogens and protozoal infectious diseases". In: *Frontiers in Cellular and Infection Microbiology* 12 (2022), p. 882995.

[12] Fahim Rahman. ""Smart Trap": A Portable Device for Real-Time Mosquito Capturing and Classification Using Image-Based Analysis". MA thesis. University of South Florida, 2025.

[13] Rishika Kapoor. “Malaria Detection Using Deep Convolution Neural Network”. MA thesis. University of Cincinnati, 2020.

[14] Tamal Kumar Kundu, Dinesh Kumar Anguraj, and Debnath Bhattacharyya. “Utilizing image analysis with machine learning and deep learning to identify malaria parasites in conventional microscopic blood smear images”. In: *Traitement du Signal* 41.1 (2024), p. 343.

[15] Veerayuth Kittichai et al. “A novel approach for identification of zoonotic trypanosome utilizing deep metric learning and vector database-based image retrieval system”. In: *Heliyon* 10.9 (2024).

[16] Issac Neha Margret and K Rajakumar. “Deep learning techniques for analyzing peripheral blood smears: a meta-analysis”. In: *Neural Computing and Applications* (2025), pp. 1–27.

[17] A Vijayalakshmi. “Deep learning approach to detect malaria from microscopic images”. In: *Multimedia Tools and Applications* 79.21 (2020), pp. 15297–15317.

[18] S Aanjan Kumar et al. “Application of hybrid capsule network model for malaria parasite detection on microscopic blood smear images”. In: *Multimedia Tools and Applications* 84.7 (2025), pp. 3459–3485.

[19] Navya KT, Keerthana Prasad, and Brij Mohan Kumar Singh. “Analysis of red blood cells from peripheral blood smear images for anemia detection: a methodological review”. In: *Medical & biological engineering & computing* 60.9 (2022), pp. 2445–2462.

[20] Barkha Kakkar et al. “Artificial intelligence-based approaches for detection and classification of different classes of malaria parasites using microscopic images: a systematic review”. In: *Archives of Computational Methods in Engineering* 30.8 (2023), pp. 4781–4800.

[21] Veerayuth Kittichai et al. “A deep contrastive learning-based image retrieval system for automatic detection of infectious cattle diseases”. In: *Journal of Big Data* 12.1 (2025), p. 2.

[22] Veerayuth Kittichai et al. “Automatic identification of medically important mosquitoes using embedded learning approach-based image-retrieval system”. In: *Scientific Reports* 13.1 (2023), p. 10609.

[23] Nouar AlDahoul et al. “Parasitic egg recognition using convolution and attention network”. In: *Scientific Reports* 13.1 (2023), p. 14475.

[24] Emmanuel Ahishakiye et al. “Enhancing malaria detection and classification using convolutional neural networks-vision transformer architecture”. In: *Discover Applied Sciences* 7.6 (2025), p. 612.

[25] Jhonathan Sora-Cardenas et al. "Image-Based Detection and Classification of Malaria Parasites and Leukocytes with Quality Assessment of Romanowsky-Stained Blood Smears". In: *Sensors* 25.2 (2025), p. 390.

* *Corresponding author*: piyush.choudhury@somaiya.edu