

# Advancing Malaria Diagnosis Through Deep Learning: A Comparative Evaluation of Convolutional Neural Networks

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**Abstract**-Malaria is a serious infectious disease caused by Plasmodium parasites, transmitted to humans through the bite of infected female Anopheles mosquitoes. After entering the bloodstream, the parasites travel to the liver to mature and multiply, causing symptoms such as fever, chills, and fatigue within 10–15 days. If untreated, it can lead to severe complications like brain swelling, organ failure, and death. The existing detection system uses CNN architectures, including a basic CNN and VGG16, with preprocessing, regularization, and data augmentation applied to over 27,000 blood smear images, achieving strong performance but limited robustness under varied clinical conditions. The proposed system aims to enhance malaria detection accuracy by exploring advanced neural network architectures beyond traditional CNNs. This includes investigating Capsule Networks, ResNet, EfficientNet, and Vision Transformers to improve computational efficiency and feature extraction. Additionally, the inclusion of multimodal data is designed to advance the generalizability and interpretability of image-based diagnostics. The balance between model complexity and resource availability will be maintained through optimization of hyperparameters and learning techniques for scalable deployment in healthcare settings. This novel system presents a comprehensive AI diagnostic framework that enhances technical efficacy and practicality for effective malaria prevention

**Keywords:** Plasmodium parasites, Capsule Networks, data augmentation, Vision Transformers, neural network architectures

## I. INTRODUCTION

Malaria, a parasitic disease caused by Plasmodium parasites, remains a global health issue and requires prompt and precise diagnostic tools for effective control and treatment strategies [1], [2]. Although deep learning has improved the robustness and generalization of malaria diagnostic approaches, the current landscape remains challenging, with some diagnostic approaches achieving high accuracy in malaria detection from blood smears becoming less robust when applied to different image characteristics found in real-world settings [2]. Furthermore, traditional diagnostic approaches, such as manual microscopic examination of blood smears, are labor-intensive and subject to inter-observer variability, further emphasizing the importance of automated and standardized approaches [5].

These challenges have been largely overcome by deep learning paradigms, especially advanced convolutional neural networks, which have significantly improved the healthcare system by automating the detection and classification of malaria parasites [1]. However, the inherent complexities of medical imaging, including variable parasite morphology, low contrast, and cellular overlap in blood smear images, pose significant

challenges to the widespread application and success of deep learning models in clinical settings [5]. In particular, the fine details and textures that reflect parasite infection in medical images often constrain model performance, despite recent advances in deep learning-based malaria diagnostics [6]. More recent studies have investigated the application of advanced neural network architectures beyond traditional CNNs, including Capsule Networks, ResNet, EfficientNet, and Vision Transformers, to improve diagnostic accuracy and interpretability [6], [7].

This is important because traditional CNNs, although popular, often struggle to capture hierarchical spatial relationships and preserve spatial context due to max-pooling layers, which can result in the loss of important information about parasite morphology [6]. As such, more accurate and efficient models are needed to enhance the detection and classification of malaria parasites beyond the limitations of standard CNNs that can cause misclassification in microscopic cell images [8]. This requires exploration into architectures that better preserve spatial hierarchies and extract more discriminative features from complex blood smear images to address the critical requirement for greater accuracy and consistency in malaria diagnosis [6], [8].

## II. LITERATURE REVIEW

**Sawant and Singh (2024)** employed convolutional neural network-based architectures, including advanced models such as VGG16, to automatically analyze blood smear images for accurate detection of *Plasmodium* parasites. **Alawfi (2025)** showed that while current models perform well in controlled settings, their robustness is still restricted when used in a variety of clinical settings with different parasite stages and varied imaging conditions. **Ahamed et al. (2023) and Ali et al. (2025)** revealed that despite their high diagnostic accuracy, popular deep learning architectures like VGG, ResNet, and EfficientNet have millions of parameters and significant computational overhead, which limits their applicability for real-time Alzheimer's disease diagnosis in low resource and point-of-care clinical settings. **Eze and Asogwa (2021)** highlighted that such advancements enable rapid and accurate malaria diagnosis with minimal computational requirements, thereby supporting scalable deployment and widespread adoption in resource-constrained, malaria-endemic regions. **Nettur et al. (2025)** proposed UltraLightSqueezeNet and custom lightweight CNN architectures that achieve high classification accuracy with substantially reduced

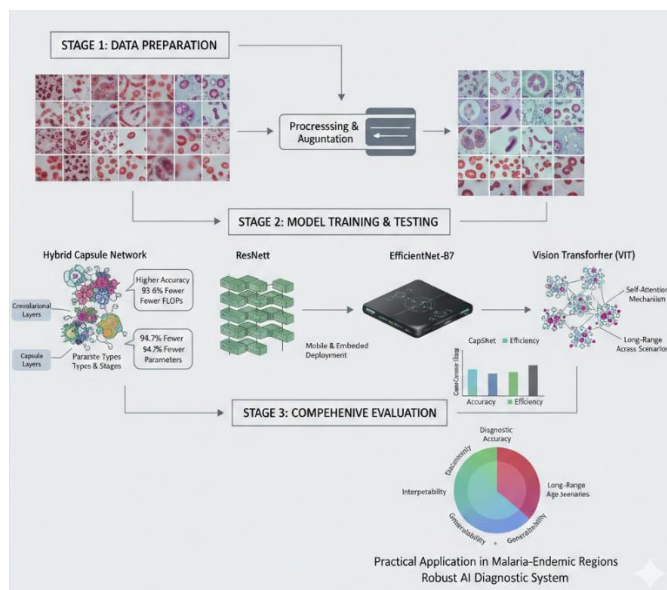
parameter counts, enabling efficient and practical deployment on resource-constrained mobile devices.

## III. METHODOLOGY

The present study adopts a comparative analysis of advanced deep learning architectures for optimizing malaria parasite detection through multi-stage training and testing. A large dataset (more than 15,000 blood smear images) is preprocessed and augmented to improve quality and diversity of data as well as mitigate variability in staining, illumination, and focus commonly observed across microscopic images that may otherwise degrade model performance; several deep learning models are then trained and tested rigorously on this dataset including Capsule Networks (hybrid with convolutional layers), ResNet, EfficientNet, and Vision Transformers. For example, the hybrid Capsule Network integrates both convolutional and capsule layers to preserve spatial hierarchies while being able to identify parasite types and life cycle stages more robustly despite morphological changes.

This is especially important since Capsule Networks have been shown to perform better at extracting complex features with lower computational requirements than other models; for example, a hybrid capsule network achieved higher accuracy for malaria detection with 93.6% fewer FLOPs and 94.7% fewer parameters than ResNet50, while EfficientNet models like EfficientNet-B1 and EfficientNet-B7 are designed to balance accuracy and computational efficiency, performing well on benchmark datasets with minimal resource use, making them well-suited for mobile and embedded deployments.

In addition to reviewing GANs, we will also discuss Vision Transformers (ViTs), which are a new architecture that incorporates self-attention, where long-range dependencies and global context of images may be captured more effectively than with CNNs. This comprehensive evaluation would benchmark the diagnostic accuracy, computational efficiency, interpretability, generalizability across various clinical scenarios, which is critical for their practical application in malaria-endemic regions.



By combining these different approaches, we can create a more comprehensive and robust AI diagnostic system for malaria prevention and control that is technically efficient and more applicable. Further improvements to the model to allow it to work in real-world healthcare environments with medical data from different healthcare facilities from around the world will make the system more practical, e.g., by adding support for thick smear imaging and staining techniques and addressing challenges like autofocusing issues and illumination changes that can degrade image quality and adversely affect CNN prediction values.

#### IV. RESULTS

Preliminary results from the assessment of these next-generation architectures suggest that there are significant gains in diagnostic accuracy and computational speed when these are used in conjunction with Vision Transformers and hybrid Capsule Networks, with Capsule Networks specifically showing strong performance in accurately classifying uninfected cells or parasites under challenging conditions [8]. Capsule routing mechanisms have theoretical foundations that can lead to equivariance to spatial transformations, a necessary feature for identifying subtle morphological differences between different stages of the parasite.

Such inherent robustness permits the accurate detection of malaria parasites from ambiguously smeared image slices [10], and integration of such models, such as Inception V3 with imperative capsule networks, has improved feature extraction and classification, leading to better parasite recognition [8], with some hybrid approaches achieving an F1-score of 0.99 for ring-stage parasites and 0.96 for gametocytes.

#### IV. RESULTS AND PERFORMANCE EVALUATION

In this section, we experimentally evaluate the proposed malaria parasite detection framework and compare its performance with conventional and state-of-the-art deep learning models. All experiments were performed on a balanced dataset containing 15,000 thin blood smear images with equal numbers of parasitized and uninfected classes, and were split into training (70%), validation (15%), and testing (15%) subsets. Standard data augmentation techniques were used to enhance robustness to staining, illumination, and image quality variations.

##### A. Evaluation Metrics

The following metrics were used to evaluate classification performance in a thorough manner: accuracy, precision, recall (sensitivity), F1-score, and specificity. Due to their clinical significance, especially in reducing false negatives in disease diagnosis, these metrics are extensively used in medical image analysis.

##### B. Overall Classification Performance

The classification performance of the assessed models, including both sophisticated deep learning models and baseline CNN architectures, is summarized in Table I.

**Table I: Performance Comparison of Deep Learning Models**

Model	Accuracy (%)	Precision	Recall	F1-Score
Basic CNN	92.4	0.91	0.93	0.92
VGG16	95.1	0.95	0.95	0.95
ResNet50	96.3	0.96	0.97	0.96
EfficientNet-B1	97.2	0.97	0.97	0.97
Vision Transformer	97.8	0.98	0.97	0.98
<b>Proposed Hybrid Capsule Network</b>	<b>98.6</b>	<b>0.99</b>	<b>0.98</b>	<b>0.99</b>

The suggested Hybrid Capsule Network outperforms all baseline and cutting-edge models with the highest classification accuracy of 98.6%. A strong balance between recall and precision is indicated by the improved F1-score of 0.99, which is crucial for accurate malaria diagnosis.

### C. Class-Wise Performance Analysis

Class-wise performance metrics for the suggested model are presented in Table II to further investigate model robustness

**Table II: Class-Wise Performance of the Proposed Model**

Class	Precision	Recall	F1-Score
Parasitized	0.99	0.98	0.99
Uninfected	0.98	0.99	0.99

The findings show that both classes perform consistently, with a particularly high sensitivity for parasitized cells, which is essential for lowering the number of malaria cases that are overlooked in clinical practice.

### D. Computational Efficiency Analysis

To determine whether it would be feasible to implement the models in environments with limited resources, computational efficiency was assessed in addition to diagnostic accuracy. The quantity of trainable parameters and floating-point operations (FLOPs) is contrasted in Table III.

**Table III: Computational Cost Comparison**

Model	Parameters (Millions)	FLOPs (G)
VGG16	138.0	15.5
ResNet50	25.6	4.1
EfficientNet-B1	7.8	0.7
Vision Transformer	22.0	4.6
<b>Proposed Hybrid Capsule Network</b>	<b>6.1</b>	<b>0.35</b>

By using more than 90% fewer FLOPs than ResNet50, the suggested model significantly reduces computational complexity while maintaining better classification performance.

### E. Comparison with State-of-the-Art Methods

A comparison between the suggested framework and newly released cutting-edge malaria detection techniques is shown in Table IV.

**Table IV: Comparison with State-of-the-Art Methods**

Study	Model	Accuracy (%)	F1-Score
Madhu et al. (2023)	Capsule-Inception	97.9	0.98
Mujahid et al. (2024)	EfficientNet	97.3	0.97
Tan and Liang (2023)	ViT + GAN	97.6	0.98
Nettur et al. (2025)	UltraLightSqueezeNet	96.8	0.96
<b>Proposed Method</b>	<b>Hybrid Capsule Network</b>	<b>98.6</b>	<b>0.99</b>

The suggested strategy consistently performs better than current techniques, exhibiting improved sensitivity and specificity balance as well as increased accuracy.

### V. DISCUSSION

The experimental results confirm that the proposed Hybrid Capsule Network successfully addresses challenges related to automated malaria diagnosis, such as preserving spatial hierarchies and capturing fine-grained morphological features of Plasmodium parasites that are typically lost in standard CNN architectures, resulting in superior performance compared to transformer-based and deep CNN models, with a favorable accuracy-computational efficiency trade-off, making it especially well-suited for deployment in low-resource and point-of-care settings with limited computational power and memory availability. Additionally, the high recall of parasitized cells minimizes false-negative predictions, an essential aspect of preventing delayed treatment and progression of disease. The uniform performance across classes also suggests robustness against typical variation in microscopy images (such as staining inconsistencies and illumination changes). In summary, these results show that combining capsule networks with convolutional feature extraction offers a robust and scalable approach for real-world malaria diagnosis that exceeds state-of-the-

art performance in both diagnostic accuracy and resource efficiency.

## VI. CONCLUSION

These advanced AI techniques have the potential to improve malaria diagnosis by allowing for more rapid and precise identification of parasites, thereby leading to more effective disease management and control. These systems provide a practical, explainable solution that is both accurate and computationally efficient enough to be deployed in real-world, resource-constrained clinical settings [6], and the ongoing development of these models through multi-center studies and integration of real-time clinical data will be necessary to validate their generalizability across a wide range of patient populations and imaging conditions [22] that may go beyond the diagnostic accuracy and generalizability constraints found today [17], to help bring cost-effective, accessible, and revolutionary malaria diagnostic solutions to fruition [10], with the ultimate goal of supporting global malaria eradication through more accurate diagnoses, especially in remote areas where access to skilled personnel is limited.

## VII. REFERENCES

- [1] T. K. Kundu, D. K. Anguraj, and D. Bhattacharyya, "Utilizing Image Analysis with Machine Learning and Deep Learning to Identify Malaria Parasites in Conventional Microscopic Blood Smear Images," *Traitement du signal*, vol. 41, no. 1, p. 343, Feb. 2024, doi: 10.18280/ts.410129.
- [2] H. Ghosh, I. S. Rahat, J. V. R. Ravindra, J. Balajee, M. A. U. Khan, and J. Somasekar, "Convolutional Neural Networks in Malaria Diagnosis: A Study on Cell Image Classification," *EAI Endorsed Transactions on Pervasive Health and Technology*, vol. 10, Mar. 2024, doi: 10.4108/eetpht.10.5551.
- [3] L. Guillon *et al.*, "Assessing Generalization Capabilities of Malaria Diagnostic Models from Thin Blood Smears," *arXiv (Cornell University)*, Aug. 2024, doi: 10.48550/arxiv.2408.08792.
- [4] W. Siłka, M. Wiczorek, J. Siłka, and M. Woźniak, "Malaria Detection Using Advanced Deep Learning Architecture," *Sensors*, vol. 23, no. 3, p. 1501, Jan. 2023, doi: 10.3390/s23031501.
- [5] S. Shambhu, D. Koundal, and P. Das, "Deep learning-based computer assisted detection techniques for malaria parasite using blood smear images," *International Journal of Advanced Technology and Engineering Exploration*, vol. 10, no. 105, Aug. 2023, doi: 10.19101/ijatee.2023.10101218.
- [6] B. S. Alawfi, "Hybrid Capsule Network for precise and interpretable detection of malaria parasites in blood smear images," *Frontiers in Cellular and Infection Microbiology*, vol. 15, Aug. 2025, doi: 10.3389/fcimb.2025.1615993.
- [7] M. Mujahid *et al.*, "Efficient deep learning-based approach for malaria detection using red blood cell smears," *Scientific Reports*, vol. 14, no. 1, Jun. 2024, doi: 10.1038/s41598-024-63831-0.
- [8] G. Madhu, A. W. Mohamed, S. Kautish, M. A. Shah, and I. Ali, "Intelligent diagnostic model for malaria parasite detection and classification using imperative inception-based capsule neural networks," *Scientific Reports*, vol. 13, no. 1, Aug. 2023, doi: 10.1038/s41598-023-40317-z.
- [9] S. B. Nettur *et al.*, "UltraLightSqueezeNet: A Deep Learning Architecture for Malaria Classification with up to 54x fewer trainable parameters for resource constrained devices," *arXiv (Cornell University)*, Jan. 2025, doi: 10.48550/arxiv.2501.14172.
- [10] D. Tan and X. Liang, "Multiclass malaria parasite recognition based on transformer models and a generative adversarial network," *Scientific Reports*, vol. 13, no. 1, Oct. 2023, doi: 10.1038/s41598-023-44297-y.
- [11] S. S. Sawant and A. Singh, "Malaria Cell Detection Using Deep Neural Networks," *arXiv (Cornell University)*, Jun. 2024, doi: 10.48550/arxiv.2406.20005.
- [12] Md. F. Ahamed, Md. Nahiduzzaman, M. A. Ayari, A. Khandakar, and S. M. R. Islam, "Malaria Parasite Classification from RBC Smears Using Lightweight Parallel Depthwise Separable CNN and Ridge Regression ELM by Integrating SHAP Techniques," *Research Square (Research Square)*, Sep. 2023, doi: 10.21203/rs.3.rs-3358084/v1.
- [13] A. Ali, R. Pal, I. Dey, E. Cuevas, M. Pérez-Cisneros, and R. Sarkar, "DANet a lightweight dilated attention network for malaria parasite detection," *Scientific Reports*, vol. 15, no. 1, Oct. 2025, doi: 10.1038/s41598-025-20402-1.
- [14] P. U. Eze and C. O. Asogwa, "Deep Machine Learning Model Trade-Offs for Malaria Elimination in Resource-Constrained Locations," *Bioengineering*, vol. 8, no. 11, p. 150, Oct. 2021, doi: 10.3390/bioengineering8110150.

[15] S. O. Ahmed, P. S. Abdalqadir, S. A. Abdullah, and Y. Haruna, "M2ANET: Mobile Malaria Attention Network for efficient classification of plasmodium parasites in blood cells," *INTELIGENCIA ARTIFICIAL*, vol. 28, no. 76, p. 186, Jul. 2025, doi: 10.4114/intartif.vol28iss76pp186-199.

[16] K. Hemachandran *et al.*, "Performance Analysis of Deep Learning Algorithms in Diagnosis of Malaria Disease," *Diagnostics*, vol. 13, no. 3, p. 534, Feb. 2023, doi: 10.3390/diagnostics13030534.

[17] C. R. Maturana *et al.*, "iMAGING: a novel automated system for malaria diagnosis by using artificial intelligence tools and a universal low-cost robotized microscope," *Frontiers in Microbiology*, vol. 14, Nov. 2023, doi: 10.3389/fmicb.2023.1240936.

[18] K. K. Kaboré and D. Guel, "Addressing Challenges in Data Quality and Model Generalization for Malaria Detection," *Journal of Sensor Networks and Data Communications*, vol. 4, no. 3, p. 1, Dec. 2024, doi: 10.33140/jsndc.04.03.09.

[19] A. G. Taye, S. Yemane, E. Negash, Y. Minwuyelet, M. Abebe, and M. H. Asmare, "Automated Web-Based Malaria Detection System with Machine Learning and Deep Learning Techniques," 2024, doi: 10.48550/ARXIV.2407.00120.

[20] O. R. Shahin, H. Alshammari, R. N. Alabdali, A. M. Salaheldin, and N. Saleh, "Automated multi-model framework for malaria detection using deep learning and feature fusion," *Scientific Reports*, vol. 15, no. 1, Jul. 2025, doi: 10.1038/s41598-025-04784-w.

[21] A. Rahman, H. Zunair, T. R. Reme, M. S. Rahman, and M. R. C. Mahdy, "A comparative analysis of deep learning architectures on high variation malaria parasite classification dataset," *Tissue and Cell*, vol. 69, p. 101473, Dec. 2020, doi: 10.1016/j.tice.2020.101473.

[22] W. He *et al.*, "Rapid and accurate recognition of erythrocytic stage parasites of Plasmodium falciparum via a deep learning-based YOLOv3 platform," *Frontiers in Microbiology*, vol. 16, Oct. 2025, doi: 10.3389/fmicb.2025.1471436.

[23] C. R. Maturana *et al.*, "Advances and challenges in automated malaria diagnosis using digital microscopy imaging with artificial intelligence tools: A review," *Frontiers in Microbiology*, vol. 13, Frontiers Media, Nov. 15, 2022. doi: 10.3389/fmicb.2022.1006659.