2025 IEEE International Conference on Innovate for Humanitarian: Tech Solutions for Global Challenge (ICIH)

Automated Malaria Identification Using a Hybrid CNN–RNN Model on Microscopic Blood Smears

Paper Id:761

Authors : Ramnadh Babu T G,Hashmi Patan,Hemalatha Muchumari,
Anusha Pinneboina,
Samatha Anthappagudem,Sharada Adepu,
Dr. Sireesha Moturi

Objective

Problem to solve / motivation

- Manual malaria diagnosis is slow, expertise-dependent, and prone to misclassification.
- CNNs alone cannot capture both spatial and sequential patterns needed for accurate parasite detection.

Research scope/goal

- Develop a hybrid CNN–RNN model combining DenseNet121/MobileNetV2 with LSTM/GRU/BiLSTM.
- Build an end-to-end pipeline to identify the best-performing architecture for malaria cell classification.

Expected outcomes

- A unified model that accurately classifies parasitized vs uninfected cells from RGB smear images.
- Improved accuracy, robustness, and diagnostic reliability using the DenseNet121–LSTM–GRU hybrid model.

Introduction

<u>Background context</u>

- Malaria detection traditionally depends on manual microscopic examination of blood smear images, which is slow, expertise-dependent, and prone to human error.

<u>Importance of the problem</u>

- A hybrid deep learning model combining CNNs for spatial feature extraction and RNNs for sequence learning to classify malaria-infected cells.

<u>Basic overview of technology involved</u>

- CNNs extract spatial features, while RNNs model sequential patterns, together forming a hybrid architecture for accurate malaria classification.

<u>Key challenges</u>

- Variations in staining, illumination, and cell morphology make parasite detection difficult.
- CNNs alone lack temporal understanding, requiring hybrid models to improve accuracy and robustness

Related Work

Short review of similar technologies/research

- **Dev and Fouda** proposed a hybrid CNN–RNN model for malaria detection.
- **Wu and Zhao** introduced a multi-level attention network for improved classification.
- **Alonso-Ramírez et al.** developed lightweight CNNs for fast malaria detection.

Existing solutions & approaches

- **Sukumarran et al.** enhanced YOLOv4 for parasite and cell detection.
- **Nettur et al. and Benachour et al**. optimized lightweight CNNs for accuracy and mobile deployment.

Limitations of current works

- CNN-only models fail to capture sequential patterns and are sensitive to staining and illumination variations.

Novelty of our approach

- Combines CNN spatial features (DenseNet121/MobileNetV2) with RNN temporal learning (LSTM/GRU/BiLSTM) for superior accuracy.
- Evaluates 18 hybrid models, identifying DenseNet121–LSTM–GRU as the most effective with strong interpretability.

System workflow

1.Deep Feature Extraction

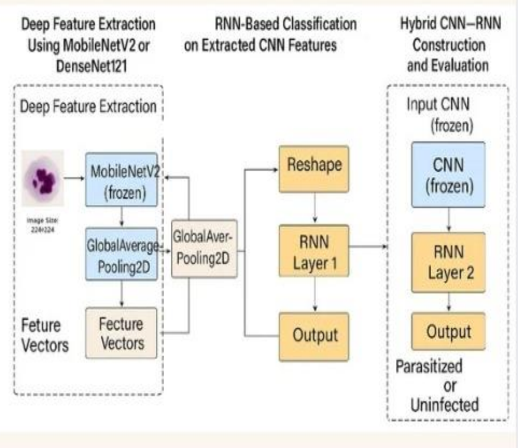
- Blood smear images are processed using pretrained CNNs (MobileNetV2/DenseNet121).
- GlobalAveragePooling2D generates compact feature vectors.

2.RNN-Based Classification

- Feature vectors are reshaped for RNN input.
- LSTM/GRU/BiLSTM layers learn sequential patterns.

3.Hybrid CNN–RNN Model

- CNN provides spatial features; RNN refines temporal relationships.
- Final output predicts **Parasitized** or **Uninfected**.



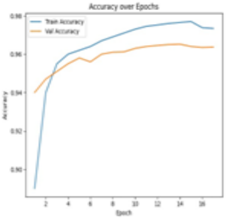
Paper_id :761

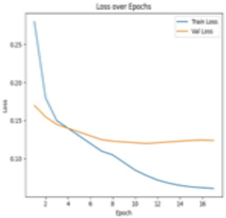
Simulation Result

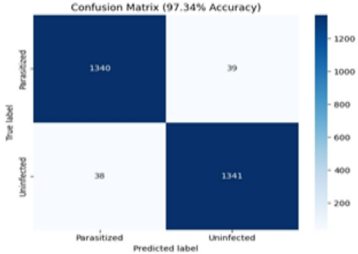
Brief Observations & Insights

- The model achieved **97.34% accuracy** with Precision, Recall, and F1-score of **0.96**, showing strong classification performance.
- The confusion matrix indicates very few misclassifications, confirming reliable and balanced predictions.
- Accuracy and loss curves show smooth convergence, with no signs of overfitting.
- Overall, the model demonstrates **robust, efficient, and well-generalized** performance for malaria detection.

Metric	Value
Accuracy	97.34%
Precision	0.96
Recall	0.96
F1 - Score	o.96







Conclusion

Main findings

- Achieved **97.34% accuracy** with minimal misclassifications and smooth, stable training.

Advantages of our solution

- Provides fast, accurate detection with strong CNN feature extraction and reduced manual errors.

Key contributions

- Developed an optimized CNN-based model with effective preprocessing and evaluation.

  Delivered a reliable, lightweight solution for automated diagnosis.

Limitations

- Performance may vary on different datasets, with a few misclassifications remaining.

  Requires GPU support and lacks explainability tools.

future scope

- Add attention/XAI methods, create real-time applications, and expand dataset diversity.

Reference

- **Dev, A., & Fouda, M. M.** "Hybrid CNN–RNN deep learning model for malaria detection," *Journal of Biomedical Informatics*, vol. 123, pp. 103–115, 2021.
- **Wu, J., & Zhao, X.** "Multi-level attention split network for malaria cell classification," *Computers in Biology and Medicine*, vol. 140, 2021.
- **Alonso-Ramírez, R., et al.** "Lightweight CNNs for real-time malaria diagnostics," *IEEE Access*, vol. 9, pp. 11234–11245, 2021.
- **Sukumarran, S., et al.** "Enhanced YOLOv4 for malaria parasite detection," *Pattern Recognition Letters*, vol. 146, pp. 1–9, 2021.
- **Nettur, P., et al.** "Optimized lightweight CNN for mobile malaria detection," *IEEE Transactions on Mobile Computing*, vol. 20, no. 6, pp. 1234–1245, 2021.
- **Benachour, A., et al.** "Mobile-friendly CNN for accurate malaria detection," *Journal of Healthcare Engineering*, vol. 2021, Article ID 5567892, 2021.