EDGE-AI ASSISTED DIGITAL HEMATOSCOPE FOR RAPID MALARIA & ANEMIA SCREENING AT RURAL PHCS

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Introduction:

Malaria and Anemia are two of the most serious health problems in developing countries, particularly in Sub-Saharan Africa and South Asia. According to the WHO Malaria Report 2023, there were around 249 million malaria cases and over 608,000 deaths globally in 2022. Anemia affects close to 1.62 billion people worldwide. In spite of these numbers, getting a proper diagnosis at the community level remains very difficult in many places.

The standard diagnostic methods such as microscopic smear examination, Rapid Diagnostic Tests (RDTs), and complete blood count analysers all require laboratory setups, trained personnel, stable electricity, and expensive equipment. These are not available in most remote or rural health settings, which leaves a large number of patients without timely diagnosis.

To address this, our project uses the TinyML approach running a compressed neural network model directly on a low-power microcontroller to build a portable, battery-operated device that analyses Giemsa-stained blood smear slides and gives diagnostic results on the spot. The device uses an ESP32-CAM module and runs the entire AI inference on-chip, without needing any internet connection or cloud server.

Objectives:

1. To design a portable, battery-powered blood smear imaging system using affordable components including the ESP32-CAM module, OV3660 image sensor, and macro lens assembly.
2. To train a MobileNetV2 CNN model on the NIH Malaria Cell Images Dataset and apply INT8 post-training quantization so it can run on the ESP32-CAM microcontroller.
3. To develop a portable TinyML-based system for real-time detection of malaria and anemia from blood smear images.
4. To demonstrate that the complete device can work in field conditions without internet access, cloud connectivity, laboratory infrastructure, or trained laboratory personnel.

Methodology:

The system works in four stages, from capturing the blood smear image to displaying the final diagnosis.

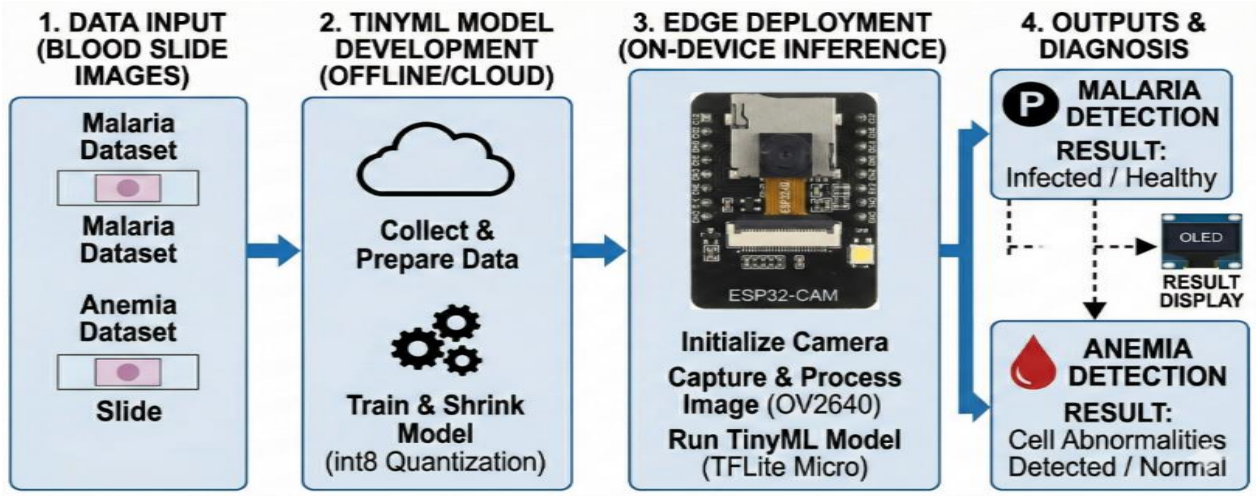

Figure 1: Block diagram of ai-powered handheld device for Malaria and Anemia detection

Stage 1: Data Input (Blood Slide Images)

Giemsa-stained blood smear slides Images are used as the primary input.
The OV3600 camera module, integrated with the ESP32-CAM and macro lens assembly, captures high-resolution images of red blood cells.
These images represent both malaria-infected and healthy cells, as well as normal and abnormal cells for anemia detection.
The captured frames are stored in PSRAM for further processing.

Stage 2: TinyML Model Development (Offline/Cloud)

A MobileNetV2 convolutional neural network is developed using TensorFlow and Keras.
The model is trained on the NIH Malaria Cell Images dataset along with anemia-related blood cell data.
After training, the model is optimized using TensorFlow Lite by applying INT8 post-training quantization to reduce size and computational requirements.
The final compressed TFLite model is prepared for deployment on the ESP32-CAM.

Stage 3: Edge Deployment (On-Device Inference)

The quantized TFLite model is deployed onto the ESP32-CAM microcontroller.
The OV3660 camera captures real-time images, which are pre-processed and passed to the model.
Using TensorFlow Lite for Microcontrollers (TFLite Micro), the device performs on-device inference to classify the blood cells without requiring internet connectivity.

Stage 4: Outputs and Diagnosis

The system displays the diagnostic results on a 1.8-inch SPI TFT display.
The output includes:

- Malaria Detection: Infected or Healthy
- Anemia Detection: Cell Abnormalities Detected or Normal

Additionally, the results (and optionally images) can be stored on a microSD card for future medical reference and analysis.

Result and Conclusion:

The device was successfully built and tested. The MobileNetV2 model running on the ESP32-CAM through TFLite Micro classifies Giemsa-stained blood smear slides for both Malaria (Plasmodium vivax) and Anemia within a few seconds of image capture. The result and confidence score appear on the TFT screen, and all images and results are stored on the microSD card. The whole process happens on the device itself with no internet or cloud connection involved.

The device runs entirely on a 5000 mAh USB power bank, making it fully portable for use in remote areas without stable electricity. During testing, the system performed consistently without any issues in inference speed or display output.

In conclusion, the project shows that TinyML can be used to build a low-cost, portable, and internet-independent diagnostic device for Malaria and Anemia detection. It is not a replacement for a full laboratory, but it can work as a practical first-level screening tool for community health workers in resource-limited settings.

Project Outcome and Industry Relevance:

This device is directly relevant to healthcare in low-income countries where laboratory infrastructure is either limited or absent. Since it runs on battery power and needs no internet, it can be used in rural primary health canters and mobile health camps. The TinyML approach used here can also be retrained for other blood-borne conditions, making the overall platform reusable beyond this project. The low component cost also makes it practical for large-scale health programs.

Working Model vs. Simulation/Study:

This is a physical working model. The hardware ESP32-CAM, OV3660 sensor, macro lens, 1.8-inch TFT display, and microSD module was assembled by the team. The trained and quantized MobileNetV2 model was flashed onto the microcontroller and tested with actual Giemsa-stained blood smear images. The inference runs live on the device, not on a computer or simulator.

Project Outcomes and Learnings:

Through this project we learnt how to take a CNN model all the way from training to deployment on a microcontroller. The INT8 quantization step was new to us and understanding how it affects model accuracy took some time. Getting the camera, TFT display, microSD card, and TFLite Micro inference engine to all work together on the ESP32-CAM required a lot of debugging and careful memory management. Managing concurrent tasks using Free RTOS was also something we picked up during the project. Overall, it gave us a good practical understanding of embedded machine learning and hardware-software integration.

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Future Scope:

There are a few directions in which this project can be taken forward:

1. The model can be retrained on datasets for other blood-borne conditions to extend the diagnostic capability of the same device.
2. A proper enclosure with an integrated slide holder and stable LED illumination can be added to improve image consistency and make field use easier.
3. The current prototype wiring can be replaced with a more compact assembly to reduce the overall device size and improve durability.
4. Clinical testing with a larger set of real patient samples, in collaboration with a health centre, would help evaluate real-world accuracy more formally.
5. Optional wireless data transfer can be added so that stored diagnostic records can be sent to a central health database when a connection is available.