

“Ai-Powered Handheld Device For Malaria And Anemia Detection”

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Abstract- This project presents a low-cost, AI-powered handheld device for detecting Malaria (*Plasmodium vivax*) and Anemia from Giemsa-stained blood smear slides. The system uses an ESP32-CAM module for edge-based inference via TensorFlow Lite for Microcontrollers (TFLite Micro), eliminating the need for cloud connectivity or laboratory infrastructure. A MobileNetV2 CNN model quantized to INT8 precision is embedded on-device to classify blood smear images and output confidence scores. Results are displayed on a 1.8-inch SPI TFT screen and logged to a 32GB microSD card. The device is powered by a 5000mAh USB power bank and is built entirely from affordable, off-the-shelf components. It is designed for use by community health workers in rural and resource-constrained settings, providing a portable, battery operated, point-of-care diagnostic tool that does not depend on internet access, trained laboratory staff, or expensive equipment.

Keywords: TensorFlow Lite Micro, Quantized Neural Networks, Embedded Systems, Internet of Medical Things.

I. INTRODUCTION

Malaria and anemia pose among the most critical public health challenges facing developing countries, primarily in regions such as Sub-Saharan Africa and South Asia. The WHO Malaria Report of 2023 states that in 2022 there were 249 million malaria cases globally, and the reported deaths were above 608,000. While at least 1.62 billion people globally are affected by anemia. Treatment is readily available for both diseases, yet the missing link in the reduction of mortality and disease burden is timely and correct diagnoses at community level.

Existing diagnostic tools can only be used to a limited extent in resource-limited and remote areas as these conventional diagnostic tools such as microscopic smear examination, Rapid Diagnostic Tests (RDTs) and complete blood count (CBC) analyzers require electricity, laboratory infrastructure and specialized personnel. Diagnostic services in primary health care centres are largely absent in rural and developing countries due to the non-availability of electricity, suitable infrastructure and equipment, which are relatively expensive.

With the emergence of the TinyML framework, the need to transmit raw data and perform complex analysis on centralized server is obsolete. The TinyML concept permits neural network inference to be implemented entirely at the "edge" on energy-efficient microcontrollers. With low-cost hardware such as the ESP32-CAM board and simple 3D printed mechanical housing, an ultra-compact digital hematoscope is possible, enabling AI driven blood smear analysis at the field, without relying on the laboratory or internet connectivity.

II. LITERATURE SURVEY

The development of handheld, AI-powered diagnostic tools is driven by the convergence of advancements in convolutional neural networks (CNNs), mobile vision, and hardware optimization. Malaria and anemia continue to pose a significant global health burden; the WHO Malaria Report 2023 estimated 249 million cases and over 608,000 deaths in 2022, while anemia affects approximately 1.62 billion people worldwide. Traditional diagnostic methods, such as microscopic smear examination and Rapid Diagnostic Tests (RDTs), are often unsustainable in remote areas due to their reliance

on centralized laboratories, stable electricity, and highly trained personnel.

Research has shown that pre-trained CNNs are highly effective feature extractors for identifying malaria parasites within microscopic images [2]. A major breakthrough in this field was the introduction of MobileNet architectures, which utilized depth wise separable convolutions to drastically reduce computational load for mobile applications [3]. This was further refined with MobileNetV2, which introduced inverted residuals and linear bottlenecks, enabling high-accuracy image classification on hardware with limited processing power [4].

The Tiny Machine Learning (TinyML) paradigm now enables the deployment of these optimized neural network inferences directly onto low-power microcontrollers, shifting computation from the cloud to the edge. Frameworks such as TensorFlow Lite Micro facilitate INT8 quantization, a process that significantly reduces model size and memory consumption while maintaining diagnostic performance on-device [5].

Recent studies highlight the ESP32-CAM as a versatile platform for Edge AI, combining a dual-core processor with integrated camera support for real-time, offline image analysis [6]. The maturation of this technology is supported by large-scale, annotated datasets, such as the NIH Malaria Cell Images Dataset, which contains 27,558 images essential for training models to distinguish between healthy and infected red blood cells [7]. Combined with digital microscopy techniques and Giemsa staining, these AI systems provide the necessary contrast to operate effectively at the point of care, successfully bridging the diagnostic gap in resource-constrained environments.

III. PROPOSED METHODOLOGY

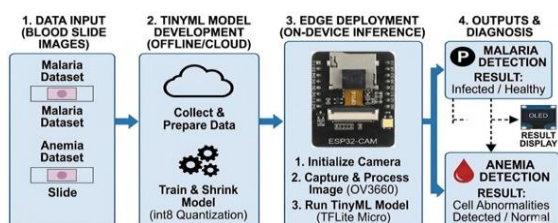


Figure 1: Ai-Powered Handheld Device For Malaria And Anemia Detection

The methodology for this AI-powered diagnostic system follows a structured TinyML pipeline designed to translate complex laboratory-grade blood analysis into a format compatible with embedded edge devices. This workflow ensures that sophisticated diagnostic capabilities can function reliably without the need for cloud infrastructure or high-end computing resources.

1. Data Acquisition and Preprocessing

The process begins with the curation of microscopic blood slide images. High-quality labelled datasets, such as the NIH Malaria Cell Images Dataset, provide the foundational ground truth for training. To ensure input consistency across the neural network, raw images undergo a preprocessing phase that includes:

- Resizing: Adjusting high-resolution micrographs to the fixed input dimensions required by the model.
- Pixel Normalization: Scaling pixel values to a specific range (typically 0 to 1 or -1 to 1) to stabilize and accelerate the learning process.

2. Model Development and Training

A lightweight Convolutional Neural Network (CNN), specifically the MobileNetV2 architecture, is selected for its high efficiency-to-accuracy ratio. The model is trained in a high-performance Python environment using deep learning libraries. This phase focuses on teaching the network to distinguish between healthy red blood cells and those infected with Plasmodium parasites or exhibiting morphological signs of anemia.

3. Optimization via Quantization

To bridge the gap between powerful training servers and the strict hardware constraints of the ESP32-CAM, the trained model undergoes INT8 quantization. This optimization step converts 32-bit floating-point weights into 8-bit integers. This process drastically reduces the model's memory footprint and computational complexity, allowing it to fit within the limited RAM and flash memory of the microcontroller while maintaining diagnostic precision.

4. Edge Deployment and Real-Time Inference

The optimized model is converted into a TensorFlow Lite Micro format and deployed onto the ESP32-CAM module. The device's hardware integration is critical:

- **Image Capture:** The onboard OV3660 camera, paired with a specialized macro-lens assembly, captures real-time images of Giemsa-stained slides.
- **Local Inference:** The microcontroller executes the neural network locally, performing classification entirely on-device.
- **Output:** The system identifies cells as "infected" or "healthy" and detects anemia abnormalities with minimal latency. Results are logged to a microSD card and displayed on an integrated SPI TFT screen for immediate, point-of-care analysis.

IV. CIRCUITE DIAGRAM

The system architecture is centered around an ESP32-CAM module, utilizing an FTDI USB-to-Serial adapter for firmware deployment where the adapter's TX/RX pins are cross connected to the module's RX/TX pins. To manage the device lifecycle, Boot Mode Selection is handled by shorting GPIO 0 to GND for Programming Mode, while removing the jumper triggers Flash Boot Mode for application execution.

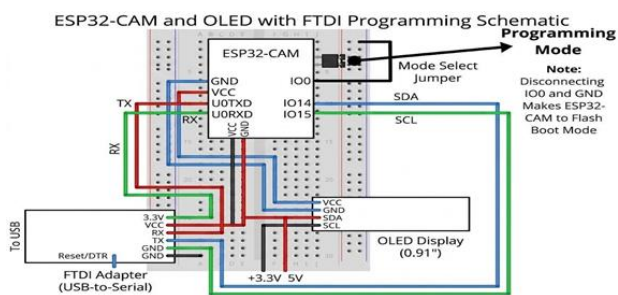


Figure 2: Circuite Diagram Of The System

Local telemetry is provided via a 0.91" OLED display interfaced through GPIO 14 (SDA) and GPIO 15 (SCL). Power is managed through a shared rail system distributing 3.3V/5V and GND from the FTDI source to all peripherals. This Compact Integration creates a streamlined footprint specifically optimized for Edge-AI applications, enabling high-performance

visual recognition and real-time data logging within a localized hardware environment.

V. RESULT AND DISCUSSION

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.

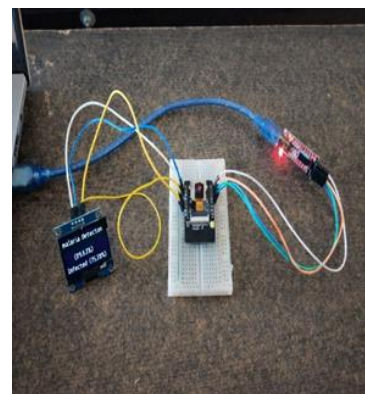


Figure 3: Malaria Infected

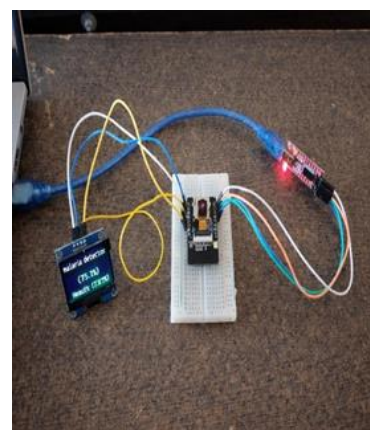


Figure 4: Malaria Healthy



Figure 5: Malaria Positive



Figure 6: Malaria Negative

VI. CONCLUSION

The development of this AI-powered handheld device marks a significant step toward democratizing healthcare in resource-constrained environments. By successfully integrating MobileNetV2 and TinyML optimization on the ESP32-CAM, the project demonstrates that sophisticated, laboratory-grade blood analysis no longer requires expensive infrastructure or high-speed connectivity. The transition from 32-bit floating-point models to INT8 quantization ensures that the system remains both lightweight and accurate, providing a sustainable alternative to traditional microscopy and costly CBC analyzers. This digital hematoscope offers more than just technological innovation; it provides a practical lifeline for community health workers in remote regions of Sub-Saharan Africa and South Asia. By

delivering immediate, offline results for malaria and anemia at the point of care, the device minimizes the critical time between diagnosis and treatment. Built from affordable, off-the-shelf components, this solution addresses the "diagnostic gap" with a scalable, battery-operated tool that empowers local clinics. Ultimately, this research underscores the transformative potential of Edge AI, proving that optimized machine learning can play a pivotal role in reducing global health disparities and saving lives in the world's most vulnerable populations.

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