Enabling real-time leprosy diagnosis on mobile devices

A study on hand temperature analysis on devices with limited compute power

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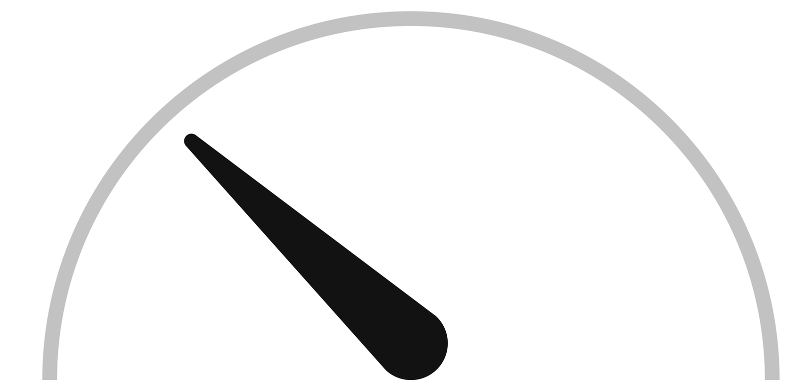
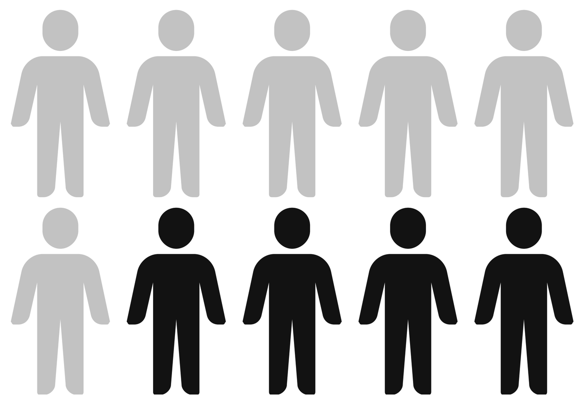


Around 200 000 new Leprosy cases are reported every year

Patients with leprosy often suffer from discrimination, social exclusion, and even denial of human rights



01 Introduction

The leprosy disease can be diagnosed based on temperature fluctuations in the hands. The current steps for this diagnosis are:

1. Film the hands using an infrared camera
2. Import the video files into python
3. Prepare the video fragments
4. Run the temperature analysis on the videos
5. Read the temperature analysis results from an excel file

02 Problems

The problems with this way of diagnosing :

- The analysis requires (many) manual steps
- The analysis needs to be run on a computer
- The analysis requires proficiency with running python scripts

Transforming the current solution to a mobile app would greatly increase the useability. However, this poses a few challenges. Mainly, running visual ai models on real-time video requires hardware with sufficient compute power, which is not always available.

03 Research Question

What methods are needed to enable real-time leprosy diagnosis on mobile devices through hand temperature analysis?

- What hand landmark detection methods are currently available for implementing real-time visual AI on infrared video?
- What techniques can be used to optimize and downsize visual AI models for mobile devices?
- What metrics can evaluate the performance and efficiency of optimized visual AI models for real-time infrared video analysis?

04 Methodology

The primary focus is on identifying techniques for implementing real-time visual AI, optimizing models for constrained hardware, and evaluating the performance of these solutions. This has been done by conducting a literature survey. Databases like the TU Delft Library, IEEE explore, ScienceDirect and Google Scholar have been used. The found papers have been grouped by the different sub-questions.

Topic	Search keywords
Real-time visual AI on infrared video	hand landmark detection, visual AI, infrared video analysis, real-time AI applications, MedidaPipe, OpenPose, YOLO multiview bootstrapping
Optimizing AI models for mobile devices	AI model downsizing techniques, quantization, pruning, AI optimization for constrained hardware. visual AI on mobiel devices weight pruning, activation pruning, filter pruning, neural architecture search Nyquist-Shannon sampling theorem, real-time visual AI, post-hoc processing
Performance metrics and evaluation	AI performance evaluation, metrics for real-time AI, mobile AI benchmarks Performance-Oriented Evaluation, Capability-Oriented Evaluation, medical AI evaluation, TEHAI framework

The used search keywords, grouped by topic

QR code for References:

05 Findings

Hand landmark models:

- MediaPipe: Lightweight, real-time, ideal for mobile, but needs domain adaptation for infrared.
- OpenPose: Accurate in complex scenarios, but computationally intensive; less suited for constrained devices.
- YOLO: High inference speed, promising for real-time, but requires adaptation for infrared imaging.

Optimization techniques

- Pruning: Reduces computational load while preserving performance.
- Quantization: Lowers precision for faster inference, with minimal accuracy loss if done carefully.
- NAS: Finds hardware-optimized architectures but is computationally expensive and requires a newly trained model.
- Adaptive Sampling: Reduces frame analysis frequency for efficiency.
- Posthoc Processing: Delegates intensive computations to post-processing, bypassing mobile hardware limitations.

Evaluation methods:

Traditional performance metrics like accuracy and latency are insufficient for mobile deployment. Capability-oriented evaluations, focusing on adaptability and domain generalization, are crucial for RGB-to-infrared transitions. Context-specific metrics, such as energy efficiency, ensure practical utility on resource-constrained devices.

06 Conclusion

Performance demands can be reduced using pruning, quantization, adaptive frame sampling, and post-processing. Especially, analyzing infrared videos at 15-second intervals and performing calculations post-recording minimizes computational load, making mobile deployment feasible. The choice of hand landmark models should prioritize capability-oriented metrics: generalization from RGB to infrared, robustness across conditions, and practical adaptability to mobile hardware.