

An Analysis of the Performance of Lightweight CNNs in the Context of Object Detection on Mobile Phones

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Abstract

Convolutional Neural Networks (CNNs) are widely used in computer vision, which is now increasingly used in mobile phones. The problem is that smartphones do not have much processing power. Initially, CNNs focused solely on increasing accuracy. High-end computing devices are most often used in this type of research. The most popular application of lightweight CNN object detection is real-time image processing, which can be found in devices such as cameras and autonomous vehicles. Therefore, there is a need to optimize CNNs for use on mobile devices. This paper presents the comparison of latency and mAP of 22 lightweight CNN models from the *MobileNet* and *EfficientDet* families measured on 7 mobile phones.

Keywords: lightweight CNNs, object detection, mobile phones, smartphones, mobile devices.

1. Introduction

Computer Vision (CV) strives to make computers perceive visual information like humans. One key task is object detection, where a computer identifies and labels objects in images using Convolutional Neural Networks (CNNs)[3, 2]. CNNs excel in image analysis by executing complex matrix operations. Thus, CV problems have been solved by high-performance devices.

On the other side, the idea of the Internet of Things assumes the presence of network communication in most everyday objects [12]. These may be devices such as TVs or speakers, but also thermostats and refrigerators. To sustain device functionality, it is necessary to use network and computing modules of miniature size. Reduced device sizes limit computing power, necessitating simplified Neural Network (NN) structures tailored for mobile devices [4]. Lightweight CNNs (LCNNs) like *MobileNet*, *EfficientDet*, *Pelee*, and *ThunderNet* are designed for swift inference in applications like autonomous cars, drones, and smartphone cameras [4].

The use of computer vision on mobile devices is now widely researched [4, 10, 14, 1, 15, 9, 16]. The aim of this work was to investigate the performance of LCNN models on various mobile phones and to answer the following research questions.

(RQ1) Which of the LCNN models achieves the highest performance on mobile phones?

(RQ2) What impact does the used computing unit have on the performance of a given model?

(RQ3) What impact does quantization optimization have on the performance of LCNNs?
We address these questions in the following sections.

2. Related Work

The *MobileNet* series stands out among CNN architectures for mobile devices. Versions by Howard et al. [6, 11, 5] are noteworthy, evaluated using the *COCO 2017* dataset for device-independent *MAdd* operation comparisons. While this metric aids theoretical model evaluation, real performance may vary based on device hardware and software.

EfficientDet by Tan et al.[13] is another architecture that is worth attention. For comparison of different models, the authors use the *FLOPs* parameter, the *AP* metric as a measure of effectiveness, and the inference time on a desktop computer's graphics card as delay in *ms*.

Ignatov et al. [7] extensively reviewed Android devices for AI capabilities, testing over 10,000 devices across 9 image processing tasks. They highlighted the advantage of *TensorFlow Lite* for standardized inferences on various smartphones. Luo et al. [8] compared mobile technologies like *PyTorch*, *Caffe2*, and *TensorFlow Lite* based on efficiency and inference time of CNN models. They tests concluded that the models behave differently on different devices, making it difficult to compare the performance of individual models, but it was found that *TensorFlow Lite* allows for the fastest model initialization by using the optimal data format.

The aforesaid works showed the dominance of *MobileNet* and *EfficientDet*, prompting our comparison of these architectures. We opted for measuring real performance through inference time in *ms* rather than focusing on parameters or operations. In contrast to high-powered GPU setups in *EfficientDet*'s work, we conducted our experiments on mobile phones. Utilizing the *TensorFlow Lite* framework aligns with its proven advantages in the literature cited [7, 8].

3. Experiments

In order to evaluate the performance of LCNNs, we examined the influence of factors such as platform, CNN model and computation unit on the accuracy and inference time. We used 7 smartphones whose abbreviated specification is shared online¹.

We performed experiments on MS Coco(*Microsoft Common Objects in Context*) which is a dataset commonly used in computer vision problems. This collection consists of 328,000 digital images depicting common objects (e.g. a person or a car) in everyday situations. A set of fifty selected photos from the COCO 2017 test set was prepared for the study.

3.1. CNN Models

For the experiment, trained CNN models are crucial. Ensuring alignment with authors' results, the following assumptions were considered to minimize discrepancies: A. models are prepared for object detection; B. it is not possible to train models or fine-tune them; C. the tested models recognize the same set of classes and were trained on the same data set; D. models are available in *tf lite* format or can be converted to this format; E. models can be run in *TensorFlow 2*. Consequently, we chose models distributed by Google in the TensorFlow Models Repository² and on the TensorFlow Hub platform³. We encountered some difficulties in using some of these models, including incompatibility between *TensorFlow 1* and *TensorFlow 2*, wrong model format or the need for train a model from scratch. Table 1⁴ collects test models.

¹<https://mostwiedzy.pl/pl/aleksandra-karpus,72346-1/lcnn-resources>

²<https://github.com/tensorflow/models>

³<https://tfhub.dev/s?deployment-format=lite&module-type=image-object-detection&tf-version=tf2>

⁴Explanation of features and model designations: *ed* - network from the *EfficientDet* family; *mn* - network from the *MobileNet* family; *_quant* - models that have been fully quantized to fixed-point representation; *_no_optimization* - models converted without

Table 1. Summary of all models used in the experiment

Model	Size	Resolution
ed-lite0_default	4.34 MB	320 × 320
ed-lite0_quant	4.34 MB	320 × 320
ed-lite1_default	5.79 MB	384 × 384
ed-lite2_default	7.20 MB	448 × 448
ed-lite3_default	11.39 MB	512 × 512
ed-lite3x_default	13.32 MB	640 × 640
ed-lite4_default	19.88 MB	640 × 640
mn-v1-300x300_default	26.02 MB	300 × 300
mn-v1-fpn-640x640_default	30.88 MB	640 × 640
mn-v1-fpn-640x640_no_optimization	118.85 MB	640 × 640
mn-v1-fpn-640x640_quant	31.0 MB	640 × 640
mn-v2-320x320_default	6.34 MB	320 × 320
mn-v2-320x320_no_optimization	23.15 MB	320 × 320
mn-v2-320x320_quant	6.42 MB	320 × 320
mn-v2-fpn-lite-320x320_default	3.51 MB	320 × 320
mn-v2-fpn-lite-320x320_no_optimization	11.22 MB	320 × 320
mn-v2-fpn-lite-320x320_quant	3.69 MB	320 × 320
mn-v2-fpn-lite-640x640_default	4.10 MB	640 × 640
mn-v2-fpn-lite-640x640_no_optimization	11.81 MB	640 × 640
mn-v2-fpn-lite-640x640_quant	4.28 MB	640 × 640
mn-v3-large_default	12.42 MB	320 × 320
mn-v3-small_default	6.86 MB	320 × 320

Diverse model sources lead to varied parameters, limiting comprehensive coefficient impact assessment on LCNN performance. Additionally, the low availability of fully quantized models reduces the generalization possibilities of the results of this type of networks.

3.2. Test Software

To assess LCNN model performance on mobile devices, we developed a Kotlin application⁵ enabling testing on CPU and GPU. Images were initially scaled to match the model's input layer size. To prevent device overheating and result degradation, we conducted single inference time measurements on a prepared image set. Latency was evaluated through the TensorFlow Lite API's inference function across all test set images, repeated for each model. Test results, including latency and detected object details, were stored in device memory for accuracy calculation later. Using ADB, the application was installed on smartphones with device optimizations before testing commenced.

4. Results and Discussion

Final latency results for each LCNN model on tested smartphones were derived from the median of all inference times. Accuracy was measured using a script for computing mAP⁶. Findings are displayed in Figure 1. Latency results exhibit a significant variation. The average inference time value is very high compared to the performance expected from the *tf-lite* models, and the standard deviation indicates large differences in the delay introduced by different models or devices. Results primarily fall within the 0ms to 744ms range, with only a few instances showing considerable delays. Figure 1 highlights that the model has a greater impact on both latency and accuracy results compared to the device. Some models like *MobileNet v1-fpn* or *EfficientDet*

using optimization (saving weights in floating-point format); *_default* models imply the use of dynamic range quantization, also called default optimization; *fpn* and *fpn-lite* means usage of a feature pyramid or a lightweight version of it; *efficientdet-lite0* is the model on which the rest of the *EfficientDet* models are based.

⁵Models and code are available at https://gitlab.com/mobile_cnn_detection_analyze_pg

⁶<https://github.com/Cartucho/mAP>

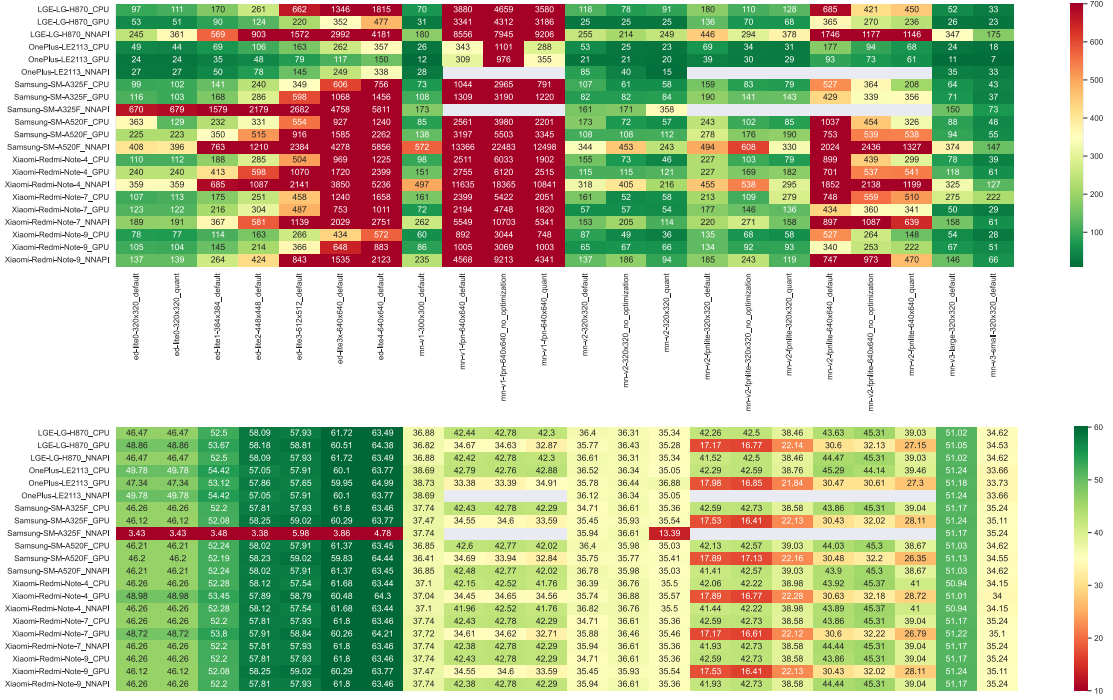


Fig. 1. Median latencies in *ms* (top) and mAP effectiveness (bottom) for all tests performed.

versions exhibit notably higher latencies. Models using FPN experience reduced accuracy on GPU execution, possibly due to discrepancies in rounding rules. The OnePlus 9 smartphone delivers superior results among tested devices due to its robust CPU and GPU capabilities.

Addressing **RQ1**, the efficiency comparison among tested architectures remains inconclusive. Different applications may benefit from distinct approaches: MobileNet emphasizes minimal inference time with acceptable mAP values, whereas EfficientDet prioritizes mAP with the lowest possible inference time. Replying to **RQ2**, quantized models outperform unquantized ones on CPUs, but GPU inference results vary unpredictably. Models with fixed-point weights showcased diverse outcomes when tested on GPUs. Answering **RQ3**, even devices without advanced graphics processors are able to obtain satisfactory results on some of the tested models thanks to optimization through quantization.

In summary, there are many ways to adapt lightweight CNNs to suit different needs. For applications in real-time systems where model accuracy is less important, *MobileNet* architecture networks are a much better choice. In turn, the *EfficientDet* architecture will work very well in systems where longer delays are acceptable, e.g. in static photo analysis.

5. Conclusions and Future Work

The study aimed to compare performance of 22 LCNN models from *EfficientDet* and *MobileNet* families on 7 mobile devices. Models ready for testing were prepared, on which various types of optimizations were made.

EfficientDet prioritized accuracy, while *MobileNet* focused on low inference time. Optimal model selection varies based on the application. Quantization optimization enables satisfactory results even on devices without advanced GPUs. Quantized models outperform unquantized ones on CPUs. Predicting quantized model inference on GPUs is challenging, with fixed-point weight models showing diverse GPU outcomes.

The work represents a small part of the LCNNs on mobile devices topic. Testing more devices can improve result applicability.

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