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Oleksandr MAMCHYC, Olesya BARKOVSKA,
Andrii KOVALENKO, Anton HAVRASHEKNO
Kharkiv National University of Radioelectronics

ANALYSIS OF EFFICIENCY OF HARDWARE PLATFROMS FOR SPATIAL ORIENTATION SYSTEMS USING A UNIFIED ENERGY CONSUMPTION MODEL

This paper addresses the problem of evaluating the efficiency of hardware platforms for spatial orientation systems, with a specific focus on mobile and assistive technologies for visually impaired users. The primary purpose is to conduct a systematic comparison between two classes of compact computing devices - single-board computers and smartphones - using a unified model and method for forecasting energy consumption in distributed computing systems that was developed and validated in our previous research. The methodology integrates both simulation and experimental measurements to provide a reliable assessment of computational performance, energy efficiency, and subsystem contributions under conditions representative of real-world computer vision workloads. The chosen experimental task was based on object detection using the SSD MobileNetV1 neural network, applied to video stream processing with standardized preprocessing and postprocessing stages, enabling reproducible and cross-platform evaluation. Energy consumption was decomposed into idle, computing, and camera subsystems, with measurements obtained through controlled power supply instrumentation over extended periods to eliminate short-term deviations. Results show that Apple smartphones consistently outperform single-board computers in both computational power and energy efficiency, with CPUs delivering significantly higher throughput and lower overall energy consumption during real-time inference, while GPU acceleration via CoreML further amplifies this advantage. Smartphones also demonstrate superior thermal stability and lower idle consumption, though their advanced camera subsystems introduce additional energy costs not observed in simpler USB cameras used with single-board platforms. The experiments shown that running similar task smartphones were underloaded and had a room for running better models, unreachable for single-board computers. The overall conclusion emphasizes that for computer vision tasks in spatial orientation systems, even older-generation smartphones represent a more efficient and practical hardware base than the most advanced single-board computers, offering not only higher performance per unit of energy but also a richer set of integrated sensors and connectivity options. These findings underline the strategic importance of smartphones as the optimal hardware foundation for next-generation assistive technologies, while pointing to future research directions involving Android platforms and peripheral expansions for single-board devices.

Keywords: distributed computing, single-board computer, smartphone, computer vision, energy efficiency.

Олександр МАМЧИЧ, Олеся БАРКОВСЬКА,
Андрій КОВАЛЕНКО, Антон ГАВРОШЕНКО
Харківський Національний Університет Радіоелектроніки

АНАЛІЗ ЕФЕКТИВНОСТІ АПАРАТНИХ ПЛАТФОРМ ДЛЯ СИСТЕМ ПРОСТОРОВОЇ ОРІЄНТАЦІЇ ІЗ ВИКОРИСТАННЯМ УНІФІКОВАНОЇ МОДЕЛІ ЕНЕРГОСПОЖИВАННЯ

У даній роботі розглянуто проблему оцінки ефективності апаратних платформ для систем просторової орієнтації, з особливим акцентом на мобільні асистивні технології для користувачів із порушеннями зору. Основною метою є проведення систематичного порівняння двох класів компактних обчислювальних пристроїв – одноплатних комп'ютерів та смартфонів – із використанням уніфікованої моделі та методу прогнозування енергоспоживання в розподілених обчислювальних системах, розроблених і перевірених у наших попередніх дослідженнях. Методологія поєднує симуляцію та експериментальні вимірювання для отримання достовірної оцінки обчислювальної продуктивності, енергоефективності та внеску підсистем в умовах, наближених до реальних навантажень комп'ютерного зору. Експериментальне завдання ґрунтувалося на виявленні об'єктів із використанням нейронної мережі SSD MobileNetV1, застосованої до обробки. Енергоспоживання було розділене на підсистеми простою, обчислень і камери, а вимірювання виконувалися за допомогою контрольованого живлення протягом тривалих періодів для усунення короткочасних відхилень. Результати показали, що смартфони Apple стабільно перевершують одноплатні комп'ютери як за обчислювальною потужністю, так і за енергоефективністю: процесори забезпечують значно вищу продуктивність і нижче загальне енергоспоживання під час роботи в режимі реального часу, тоді як прискорення GPU через CoreML ще більше підсилює цю перевагу. Смартфони також продемонстрували кращу термостабільність і нижче споживання в режимі простою, хоча їхні вдосконалені підсистеми камер мають додаткові енергетичні витрати в порівнянні з простішими USB-камерами. Загальний висновок підкреслює, що для задач комп'ютерного зору в системах просторової орієнтації навіть смартфони попередніх поколінь є більш ефективною та практичною апаратною основою, ніж найсучасніші одноплатні комп'ютери, пропонуючи не лише вищу продуктивність на одиницю енергії, але й ширший набір інтегрованих сенсорів та засобів підключення. Ці результати підкреслюють стратегічну важливість смартфонів як оптимальної апаратної основи для асистивних технологій наступного покоління та вказують на перспективні напрями подальших досліджень, що охоплюють Android-платформи та розширення периферій для одноплатних пристроїв.

Ключові слова: розподілені обчислення, одноплатні комп'ютери, смартфони, комп'ютерний зір, енергетична ефективність.

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Introduction

In recent years, the rapid development of embedded computing platforms and mobile devices has enabled new approaches to solving problems of human–machine interaction and spatial orientation, particularly for users with restricted capabilities. Computer vision, machine learning, and sensor fusion technologies have matured to the point where they can be integrated into compact, portable systems that support autonomous operation and real-time decision making. These systems are increasingly applied in assistive technologies for visually impaired individuals, navigation aids, and context-aware interfaces. However, the success of such solutions critically depends not only on the sophistication of algorithms but also on the efficiency and suitability of the underlying hardware. The interplay between computational performance, energy consumption, and device form factor determines whether a system can transition from a laboratory prototype into a practical tool for everyday use.

The problem of hardware efficiency becomes severe when designing mobile and wearable applications for spatial orientation. Unlike stationary systems, where power supply and cooling are not major limitations, portable platforms must operate under strict constraints of size, weight, and energy autonomy. The variety of hardware platforms available today creates both opportunities and challenges for system designers. On the one hand, powerful smartphones combine multicore CPUs, GPUs, dedicated neural accelerators, and high-quality sensors into a single device, offering impressive computational potential in a compact form. On the other hand, single-board computers provide an open, customizable environment, making them attractive for prototyping and specialized deployments. Each class of device has its own strengths and limitations in terms of peak performance, energy efficiency, thermal behavior, and peripheral integration. For assistive applications where uninterrupted operation and responsiveness are essential, it is therefore crucial to evaluate these platforms in a systematic and comparable manner.

The main goal of this paper is to apply a methodology used in our previous research to make a comprehensive comparison of smartphones and single-board computers power consumption under similar loads. The analysis will include simulation part and real measurements for results verifications.

State of the art

In our previous work, we developed and experimentally validated two advanced assistive and interaction-oriented systems. The first study [1] investigated mobile machine learning platforms for human gesture recognition in human–machine interaction systems, with a focus on smart home control. A hybrid local–cloud approach with optimized sensor placement was proposed to enhance recognition accuracy and adaptability under real-world conditions. However, local-cloud approach is dependent on Internet access, hence local-only approach may be preferrable here. The second study [2] addressed indoor navigation for visually impaired users, integrating computer vision–based obstacle detection, BLE localization, voice interfaces, and spatial mapping. A two-stage YOLOv8-based recognition pipeline with adaptive preprocessing was introduced, significantly improving detection metrics under noisy conditions and highlighting the need for complementary sensing (e.g., LiDAR) in challenging scenarios.

From the performance perspective, our previous works clearly demonstrate the decisive role of hardware processing power and energy efficiency in enabling high-quality, real-time operation. Gesture recognition and indoor navigation tasks both require continuous analysis of high-resolution video streams, deep learning inference, and sensor data fusion, creating substantial computational demands on mobile and embedded platforms. In the gesture recognition system, Create ML’s local processing minimized latency but depended on device CPU/GPU resources, while cloud-based solutions offered scalability at the expense of network dependency and increased energy consumption. In the navigation system, YOLOv8’s real-time inference required hardware acceleration and effective power management to remain practical for wearable or portable use. In both systems, user experience, responsiveness, and operational autonomy are directly constrained by the balance between computational performance and power efficiency.

The rapid integration of Artificial Intelligence (AI) and Computer Vision (CV) into mobile platforms has opened new opportunities for enhancing independence and quality of life among visually impaired persons (VIPs). This [3] study offers a comprehensive evaluation of four leading AI/CV-based assistive mobile applications—Microsoft Seeing AI, Envision, Supersense, and Google Lookout—across both iOS and Android ecosystems, with specific attention to parameters critical for medical and daily assistive use, such as accuracy, performance, reliability, accessibility, privacy, energy efficiency, and usability. Findings highlight that while these applications demonstrate high potential in text, object, and currency recognition, persistent challenges remain in performance under low-light conditions, multilingual support, and interface complexity. Moreover, reliance on cloud-based processing can hinder response times and battery efficiency, limiting feasibility for prolonged or offline use in personal medical contexts.

From a hardware–software integration perspective, the evaluation underscores the necessity for platform-agnostic optimizations: leveraging local datasets to reduce latency, implementing compact and intelligent image-processing engines to mitigate sensor limitations, and designing universally accessible interfaces aligned with WCAG principles. Given the diversity of user needs—especially in low-resource settings—future development must prioritize support for regional languages, stronger data privacy controls, and potential expansion into indoor navigation functionalities. For medical applications tailored to individuals with severe visual restrictions, these improvements would not only enhance diagnostic or monitoring accuracy but also ensure inclusive, reliable, and secure operation across heterogeneous device capabilities. This positions AI/CV-enabled mobile tools as a pivotal component in the broader landscape of accessible personal healthcare technologies.

Another article [4] presents a mobile-based obstacle detection system tailored for visually impaired individuals, emphasizing the adaptation of deep learning models to operate effectively on resource-constrained platforms. Traditional aids, such as canes or wearable sensor systems, offer limited detection ranges or require specialized hardware, which can hinder accessibility and usability. In contrast, the proposed approach leverages the YOLOv5s architecture, chosen for its optimal balance between real-time performance and computational efficiency, making it suitable for mobile deployment. Central to the study is the creation of the Detectra dataset, consisting of 7600 high-resolution images captured in the real-world environment of visually impaired students. The dataset, encompassing 76 obstacle classes, was annotated with precision to reflect hazards encountered in daily navigation. The best-performing model, trained over 300 epochs (YOLO-300), achieved a mAP of 0.42 and an accuracy of 76%, and was integrated into a mobile application with multimodal feedback via auditory and haptic cues. This combination of optimized detection algorithms and intuitive interaction modalities ensures timely and contextually relevant alerts, enhancing spatial awareness and autonomy. By embedding the obstacle detection capability directly into smartphones, the solution bypasses the need for additional hardware, reducing cost barriers and increasing accessibility. The study contributes to the state of the art by demonstrating how modern computer vision techniques can be adapted to heterogeneous hardware platforms for assistive medical applications, delivering robust, real-time support to individuals with visual impairments in their everyday environments.

DRISHTI [5] - a cost-effective, AI-driven wearable assistive device tailored for blind and visually impaired individuals, integrating multiple hardware platforms to convert visual cues into real-time audio guidance. Leveraging the ESP32-CAM module, smartphone-based computation, and Bluetooth-connected speakers, the system exemplifies a hybrid processing approach: lightweight image capture and wireless transmission are handled by embedded hardware, while computationally intensive tasks—object detection via YOLOv7, currency recognition using ResNet-50, text extraction with Tesseract OCR, and multilingual audio rendering through gTTS—are executed on a connected mobile platform. This architecture exploits the strengths of low-power embedded systems for portability and affordability, while outsourcing advanced analytics to a widely accessible device (the smartphone), ensuring scalability and minimal end-user cost.

From a state-of-the-art perspective, DRISHTI addresses limitations of prior solutions—such as bulkiness, high price, or poor detection accuracy—by balancing affordability with performance, and by designing with BVI users' real-world preferences in mind (e.g., wearable comfort, smartphone availability, wireless feedback). Its modular hardware-software synergy demonstrates the feasibility of mixed-platform assistive systems, where embedded microcontrollers and commodity consumer electronics collaboratively deliver context-aware navigation and object identification. Such approaches have strong potential for broader adoption, especially in low-resource settings, as they combine adaptable AI algorithms with ubiquitous hardware, lowering barriers to personal medical-grade applications for people with sensory restrictions.

An analysis of current and emerging assistive technologies for visually impaired individuals [6] focuses on integrating Artificial Intelligence (AI) and Visible Light Communication (VLC) into personal-use medical applications. Traditional aids—such as white canes, guide dogs, and Braille—have been augmented by modern hardware platforms ranging from smartphones with accessibility apps to specialized standalone devices like smart canes, wearable haptic systems, AI-driven glasses, Braille tablets, and text-to-speech readers. These tools leverage multiple sensors, connectivity options, and multimodal feedback (audio, haptic, tactile) to enhance mobility, information access, and independence. VLC offers unique advantages for assistive contexts: high-bandwidth, secure, and interference-free data transmission; precise indoor localization; and compatibility with existing lighting infrastructure, allowing cost-effective deployment. Its integration into wearable or portable platforms could enable real-time environmental mapping, object recognition, and safe navigation for blind users. AI complements this by optimizing communication links, adapting systems to user needs, recognizing hazards, and supporting early disease detection through advanced medical image analysis. The synergy between AI and VLC promises unified, context-aware assistance solutions that operate across diverse hardware—smartphones, wearable devices, and embedded platforms—maximizing accessibility and autonomy. The convergence of these technologies forms a robust state-of-the-art foundation for developing next-generation personal medical applications tailored to visually impaired individuals.

The evolution of hardware platforms for personal medical navigation applications tailored to visually impaired individuals reflects a dynamic integration of diverse sensing, processing, and feedback technologies. Wearable systems—ranging from smart glasses and haptic vests to head-mounted RGB-D cameras—offer hands-free operation, continuous environmental perception, and direct user feedback through tactile or auditory channels. Their portability and real-time adaptability make them suitable for varied environments, though challenges remain in power consumption, comfort, and data processing complexity. In contrast, non-wearable solutions such as smart canes, handheld devices, or stationary vision systems provide robust sensing with fewer ergonomic constraints but require active handling and may lack the contextual immediacy of body-mounted devices. Recent advances leverage [7] hybrid hardware platforms combining RGB-D imaging, LiDAR, ultrasonic sensing, and tactile interfaces, often linked to smartphones for computation and connectivity. Such configurations enhance obstacle detection, spatial mapping, and context-aware guidance while enabling personalization of feedback. The integration of AI-based algorithms for object recognition, path planning, and sensor fusion significantly improves system robustness and usability, even in low-light or cluttered environments. Moreover, user-centered design principles have become central, ensuring that interface modalities align with the sensory, cognitive, and ergonomic needs of blind users. This hardware-software synergy is steadily transforming assistive navigation into an accessible, adaptive, and socially inclusive tool, highlighting the necessity of continued interdisciplinary research to balance performance, affordability, and user acceptance for widespread real-world deployment.

Our previous study [8] presents a universal model for forecasting energy consumption in distributed computing systems, applicable to both stationary server-based architectures and heterogeneous networks of mobile devices. The model integrates representations of the computing system, workload, and distribution strategy, enabling accurate simulation of energy use across varied hardware environments and accounting for both computation and data transfer costs. Experimental validation confirms that the model reliably reflects the influence of hardware architecture on energy efficiency. Results demonstrate that mobile GPU-based systems can achieve higher energy efficiency than stationary GPU-based systems for parallelizable tasks, primarily due to their architecture and lower operating frequencies. The work highlights the potential of mobile devices as an energy-efficient alternative for certain classes of distributed computing workloads, while noting that model applicability may depend on task characteristics, particularly communication intensity. The methodology provides a basis for further research into energy-aware distributed computing and for extending the model to more diverse and data-intensive scenarios.

Based on listed points, it seems very essential to understand strong and weak points of hardware we use to run software. In our research we're going to pay the most attention to comparison of 2 classes of devices very suitable for application of compact personal mobile computers running software helping impaired people.

There are not that many hardware platforms that can be used for people with restricted capabilities. Those devices must meet multiple criteria: they should be small, performant, capable of autonomous work and should be able to interact with environment and peripherals and, of course, safety. Size and performance aspects are obvious – the smaller the device is, the simpler it's integration for mobile use, the faster the device is, the heavier and better algorithms is can run, hence achieve better quality in whatever task it's used for. Capability of autonomous work is not that obvious: usually only ability to run autonomously for certain period of time is taken into account, but we're rising another parameter – the power efficiency, the amount of computing operation performed per joule of energy. This parameter is also not atomic and can be decomposed into idle or low load power efficiency and power efficiency under high load. Also, autonomous work includes accumulators and their user experience. These parameters affect lifetime of mobile device and it's requirements to a cooling system. Ability to interact with environment is pin-point here: the device should gather the data from environment and transfer it to a user. We avoid the user interface in this paper and focus only on interaction with the environment, this includes camera devices, lidars, magnetometers, accelerometers, position services such as GPS etc. Ability to interact with peripheral devices includes data transfer interfaces such as cellular networks, wired and wireless interfaces, software capabilities to interact with various devices etc.

This paper is dedicated to comparison of 2 classes of devices capable of doing all above: single board computers and mobile phones (smartphones). The research is concentrated mostly around peak performance, power consumption in idle and under similar load. Also, basic survey of other aspects will be provided.

Case study

For our research, single board computers will be represented by Raspberry Pi 5 and Orange Pi 5. Smartphones will be represented by iPhone 12 mini and iPhone 16. For performance measurement we will use methodology described in our previous research – the unified model and method for forecasting energy consumption in distributed computing systems [8].

First, we need to define a computing task. Computing task consists of video frames preprocessing, processing and postprocessing. For image processing we pick Single Shot Detector (SSD) on MobileNetV1, a neural network designed for objects detection and classification. One of the main advantages of this NN is it's capable of running on same resolver (tflite) on all platforms we need and we know its complexity is about 0.56 FLOPs [9]. Preprocessing will include resizing of frame and bringing it to a proper color space, and postprocessing will be a results decoding and drawing an overlay (figure 1).

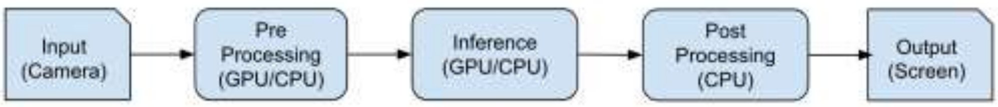

Fig 1. Structure of a computing task model for simulation

Energy consumption of computing devices can be split into 3 parts: idle consumption (power consumption of hardware itself when it's not loaded with any task), pure computing unit consumption (CPU or GPU), and peripherals consumption (camera taking video). To build a computing task model we need to isolate each of there consumers. To isolate pure computing power consumption, we will give a maximum load of computing tasks on set of frames stored in RAM. To isolate pure cameras power consumption, we will start capturing camera feed at HD 1280x720 and 30 fps, but without further processing. To isolate idle consumption, we will measure consumption of idling devices.

Power consumption measurements are done by direct powering of a particular device from laboratory power source via USB-C interface. Each measurement done in the following way: onboard accumulators are fully charged (for smartphones), no displays (screen is dimmed, display is disconnected), enabling load for at least 30 min to warm up the devices, accumulating consumption under the load for at least an hour to avoid random consumption deviations and then subtraction of idle consumption from common consumption. This approach allows us to minimize an influence of accumulators' charge/discharge, avoid short-term thermal boost effects while chips are cold and subtract idle consumption of the device from pure computing consumption. USB-C interface has a small overhead of its own. Smartphones are connected to WiFi network and single board computers are connected to LAN via wired connection, this also slightly increases the consumption. All those factors are minor and mostly the same for both types of devices, so they will not affect the comparison, however absolute numbers of consumption will be slightly higher that they actually are.

On figure 2 you can see particular consumption measurements. We didn't run the model inference on GPU on single board computers because it lacks support on Orange Pi 5 and shows unstable results on Raspberry Pi 5 since it uses only obsolete OpenGLES backend. We can see that idle consumption of single-board computers are significantly higher than smartphones, however camera consumption is lower, this is mostly because we've sticked to HD resolution which is native to the USB web camera used on single-board computers, but native resolution of both smartphones cameras is 12Mp which is then scales down and enhanced by Apple software, and we can't control this.

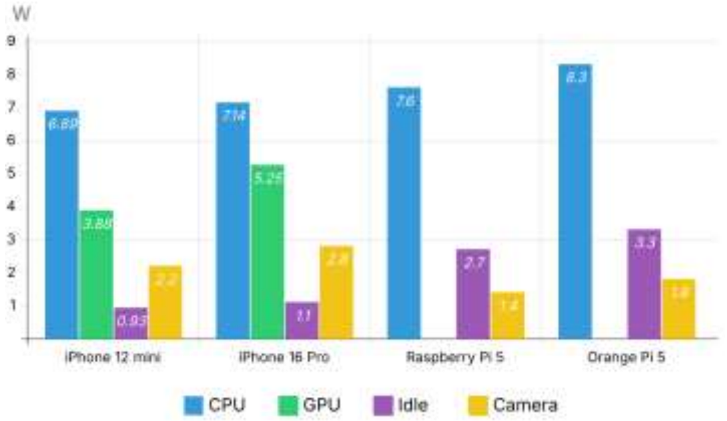

Fig 2. Measurement of power consumption of different hardware by subsystem

On figure 3 we can see the FPS comparison between single board computers and smartphones. Since the unified model and method for forecasting energy consumption in distributed computing systemsis made to compare efficiency between different devices we can stick to FPS as performance units, but if we need absolute values, we can always multiply FPS by 0.56 GFLOPs er frame.

With these data gathered we have everything we need to run simulation and compare with real world measurement. Both simulation and measurement are conducted under limit of 50 FPS so every device is capable of real-time processing. Simulation and experiment duration is 1 hour. Simulated and directly measured consumed energy is shown in figures 4 and 5 respectively.

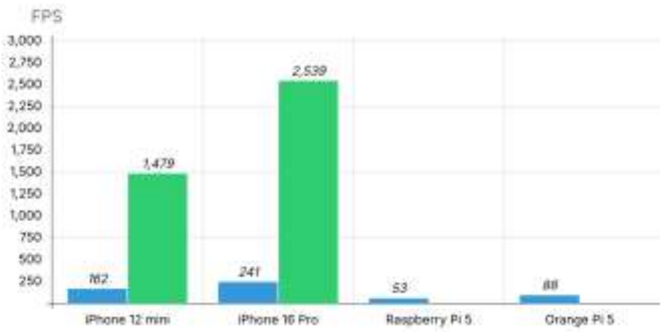

Fig 3. Peak FPS for inference for different hardware

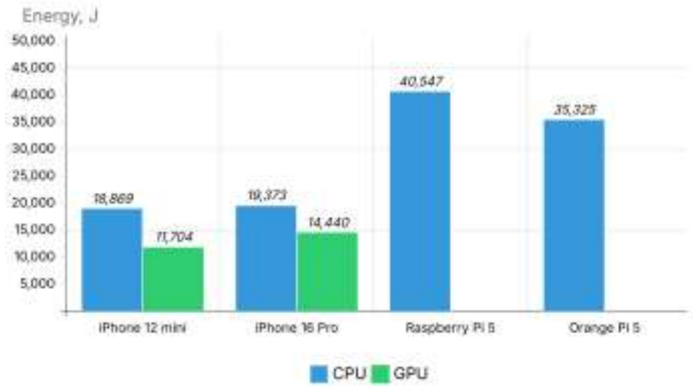

Fig 4. Simulated energy consumption of 1-hour real-time objects detection from camera stream

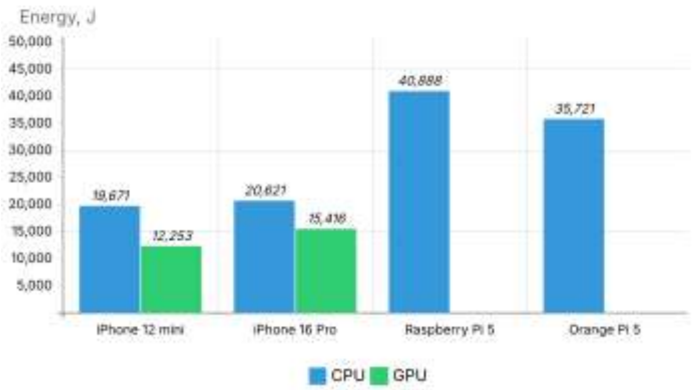

Fig 5. Measured energy consumption of 1-hour real-time objects detection from camera stream

Conclusion

We can observe some difference between simulated and measured consumed energy of mobile devices. This is known flaw of our model. Our forecasting model calculates computing unit consumption as a linear function from this computing unit load. In our case mobile devices are very underloaded, but they can't run on 1% of their performance or even on 10%, especially their GPUs. In reality this results in non-linear dependency between useful performance and actual physical consumption. For single-board computers this is not the case since they perform on near-peak performance, hence simulated data s much closer to measured.

From our research we can make several major conclusions. First, if we talk about computer vision inference models, Apple device' CPUs outperform single-board computers in times. This results in ~2 times less energy consumed over a time compared to Raspberry Pi 5 and ~1.75 times compared to Orange Pi 5. Apple GPUs outperform single-board computers in dozens of times, but only if the model is compatible with CoreML. In this case Apple device power consumption if ~2.7-3.3 times lower than Raspberry Pi 5 and ~2.3-2.9 times lower than Orange Pi 5.

Second, high contribution of idle consumption of single-board computers – even if they are idling, they consume 2.5-3.5 times more energy than ready-to-work unlocked idling Apple device. If locked, the idle mode of any smartphone is even more efficient allowing those to live for days.

Third, contribution of smartphones' camera comparing to a simple USB web camera. This is mostly related to proprietary photo and video enhancement we can't control – those features are software and drain a lot. Additionally, smartphones' cameras are of higher resolution and performance which also contributes to their power efficiency. We can conclude that camera of a smartphone is an overkill for spatial orientation, but thre is not much we can do except lowering resolution.

Forth, smartphones were significantly underloaded, which means we can run much heavier and accurate models even on CPU. For those compatible with CoreML or Metal, we can afford running models that are principally not runnable on single board computers due to bare lack of performance, and still consume less energy.

Fifth, cooling problem. Raspberry Pi 5 and Orange Pi 5 run very hot very quickly, and their only hotspot is CPU. To avoid throttling and significant performance drops vendors recommend active cooling which would contribute to power consumption and would also require a fresh air source. To avoid additional power losses, we had to install heavy copper radiator to let single board computers work without throttling and additional power consumption. It is heavy and clunky. Smartphones stay rather cold under the same load, and the heat production is distributed between multiple subsystems: (CPU, GPU, camera controller).

The final conclusion we can make: for computer vision tasks even several years old Apple smartphone will outperform best in the market single-board computer in both - pure CPU performance and consumed power. In some corner cases, when model is compatible with GPU backend, smartphone will outperform single-board computer in dozens of times, still consuming less energy. This means, smartphone-based solution for spatial orientation can run better models and work longer with similar accumulator. Additionally, any smartphone will have additional tools for spatial orientation out of the box: camera, accelerometer, gyroscope, magnetometer (compass), position system (GPS and similar) and access to Internet through cellular network. Sometimes even some additional capabilities like lidar.

This research was restricted to Apple devices, mainly due to good interfaces for GPU (Metal) and neural engine (CoreML). This means, we haven't covered Android smartphones which obviously have a lot to offer – usually even better pure CPU performance and less restrictions in implementation. This will be covered in our next researches. Also, we've only mentioned some peripherals that any smartphone has out of the box, but we haven't made a comparison with corresponding extensions single-board computers can have. This is the area where properly extended single-board computer can outperform smartphones, and this also be our goal in future researches.

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Oleksandr Mamchych **Мамчич Олександр**	PhD student at Department of Electronic Computers (ECM), Kharkiv National University of Radioelectronics, Kharkiv, Ukraine e-mail: oleksandr.mamchych@nure.ua https://orcid.org/0009-0001-6602-2929	аспірант кафедри Електронних Обчислювальних Мащин, Харківський Національний Університет Радіоелектроніки, Харків, Україна
Olesia Barkovska **Олеся Барковська**	Candidate of Technical Science, docent at Department of Electronic Computers (ECM), Kharkiv National University of Radioelectronics, Kharkiv, Ukraine, e-mail: olesia.barkovska@nure.ua https://orcid.org/0000-0001-7496-4353	кандидат технічних наук, доцент кафедри Електронних Обчислювальних Мащин, Харківський Національний Університет Радіоелектроніки, Харків, Україна
Andriy Kovalenko **Андрій Коваленко**	Doctor of Technical Science, head of Department of Electronic Computers (ECM), Kharkiv National University of Radioelectronics, Kharkiv, Ukraine e-mail: andriy.kovalenko@nure.ua https://orcid.org/0000-0002-2817-9036	доктор технічних наук, професор, завідувач кафедри Електронних Обчислювальних Мащин, Харківський Національний Університет Радіоелектроніки, Харків, Україна
Anton Havrashekno **Антон Гаврашенко**	PhD student at Department of Electronic Computers (ECM), Kharkiv National University of Radioelectronics, Kharkiv, Ukraine, e-mail: anton.havrashenko@nure.ua https://orcid.org/0000-0002-8802-0529	аспірант кафедри Електронних Обчислювальних Мащин, Харківський Національний Університет Радіоелектроніки, Харків, Україна