Thermo Presence: The Low-resolution Thermal Image Dataset and Occupancy Detection Using Edge Devices

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Abstract. Presence monitoring in office buildings is a vivid topic in building management systems. One of the well-established techniques to achieve it is using infrared sensors. In this paper, we present an annotated dataset consisting of low-resolution thermal images from different office rooms, with a changing number of persons in the scene. For each thermal image, a corresponding image from the RGB camera is available for visual inspection. On each thermal image, the centre position of every person is annotated, allowing not only to know the total number of people but also to track their positions. Along with the dataset, an evaluation of U-Net like convolution neural network architecture on low-power edge devices was carried out, with a comparison of their performance and energy consumption. Due to FLASH memory deficiencies on embedded systems, quantization of the models was applied, with an added benefit of shorter interference time. The presented solution allows estimating the presence density map while maintaining low-level power consumption.

Keywords: Thermal Imaging · Deep Learning · Edge AI .

1 Introduction

Office and industrial buildings require a lot of energy to keep comfortable conditions for people, both in terms of lightning and HVAC (heating, ventilation, air conditioning). In majority of buildings there is no presence detection systems or only a binary information, therefore a lot of energy is wasted for conditioning empty rooms. The savings of the energy from using presence sensors are estimated to be around 25% [2]. Identifying people in high-resolution RGB images is a well-established technique, but it raises serious concerns, especially regarding violation of privacy. Thanks to low-resolution and processing on the edge, the presented method allows keeping the privacy of the monitored people, with minimal security risks.

The Thermo Presence dataset presented in this paper consists of annotated low-resolution thermal images, captured from a thermal array sensor (MLX90640) at 0.5 Hz. The dataset can be used to train the models, especially with convolutional neural networks, as applied in [3]. Similar solutions are presented in [1], where the authors achieved only binary presence information, and [4], but the presented method is both more accurate and resource-efficient. Moreover, both papers did not disclose their datasets.

2 Thermo Presence Dataset Specifications

The dataset consists of thermal images with a resolution of 32x24 pixels, with annotated centres of persons. The data was gathered in four different office rooms, with a changing number of persons from 0 to 5 people on each frame. An exemplary thermal frame presented in 1 shows five people in different positions, with quite significantly varying sizes. All the gathered data were divided into training, validation and test datasets, so that each consists of frames continuous in time, with data split presented in Table 1.

Table 1. The distribution of data in Thermo Presence dataset.

Dataset	**Number of Persons in a Frame**						**Total**
	0	**1**	**2**	**3**	**4**	**5**	
Training	99	105	2984	3217	1953	114	8472
Validation	0	139	631	1691	225	139	2825
Test	162	83	211	341	1235	315	2347

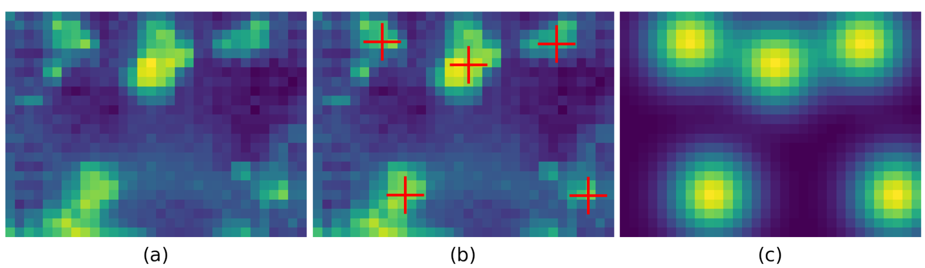

Fig. 1. Thermo Presence dataset: (a) example thermal image from dataset; (b) annotations - person locations; (c) generated density map.

3 Neural Network Architecture

The occupancy counting is a density estimation task and requires an algorithm able to reconstruct the position of persons. Therefore the concept of U-Net architecture [5] was adapted to this task objectives. Although the implemented deep learning model has a simplified, single-channel structure (see Fig. 2), the achieved values of quality measures are very high.

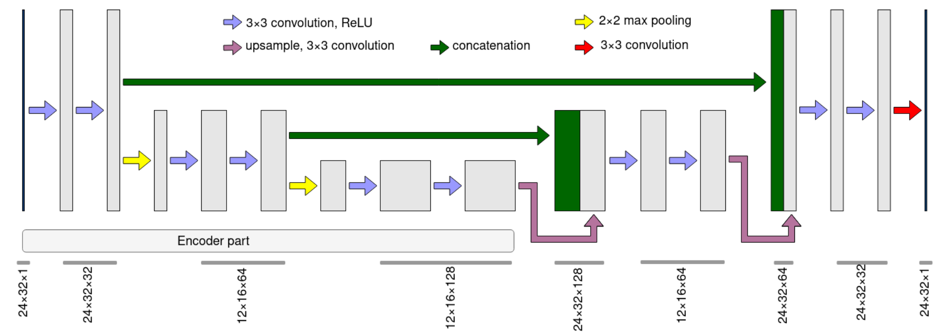

Fig. 2. The proposed U-Net based neural network architecture.

4 Evaluation

The proposed encoder-decoder algorithm was evaluated on Raspberry Pi 4B, a commonly utilized smart home hardware. Moreover, the computing accelerators: Coral USB Accelerator and Intel Neural Compute Stick 2 (NCS2), were also tested. The Coral USB Accelerator is a co-processor with an Edge TPU circuit that natively supports most of the widely used TensorFlow layers. The Intel NCS2 is also a small USB module, designed to accelerate neural networks. Its main part, Intel Movidius Myriad X Vision Processing Unit, is a dedicated hardware neural accelerator.

Table 2. Average inference time and quality measures observed on the tested hardware.

Device	**Data Format**	**Avg. Inference Time [ms]**	**MAE**	**MSE**	**Counting MAE**	**Counting MSE**
Raspberry Pi 4B	FP32	25.2894 ±0.7431	0.1205	0.0493	0.0473	0.0499
Raspberry Pi 4B	FP16	25.3226 ±0.8889	0.1204	0.0493	0.0473	0.0499
Raspberry Pi 4B	INT8	16.4497 ±0.0921	0.4733	0.3459	0.2876	0.3259
Raspberry Pi 4B + Intel Neural Compute Stick 2	FP16	3.0045 ±0.2114	0.1239	0.0507	0.0481	0.0507
Raspberry Pi 4B + Coral USB Accelerator (max)	INT8	0.7107 ±0.0601	0.4729	0.3470	0.2833	0.3208

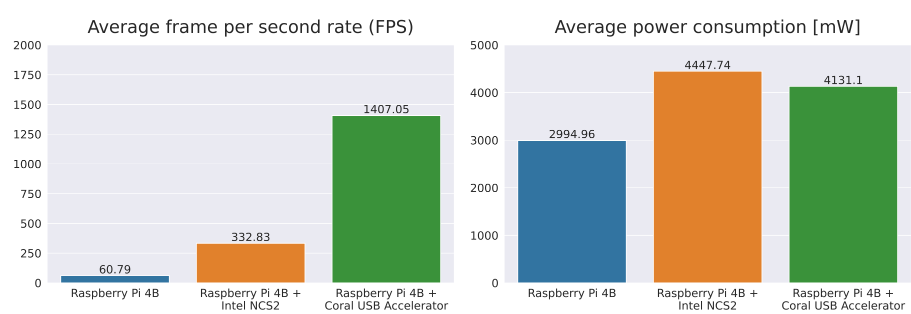

Fig. 3. The algorithm performance measurement: (left) average frame per second rate; (right) average power consumption during inference process.

The hardware evaluation includes inference time measurement and standard regression metrics like Mean Absolute Error (MAE) and Mean Squared Error (MSE) calculation. Furthermore, in the benchmark process the Counting MAE and Counting MSE metrics were introduced. This measures compares the output people count in frame instead of its elements one by one. The detailed results are presented in Table 2. In IoT applications, power consumption and efficiency are as crucial as overall algorithm performance. Therefore, the current and voltage were measured on the tested hardware. Figure 3 depicts benchmark results.

5 Discussion

The paper presents a novel dataset for presence detection and occupancy counting approaches. It consists of 13 644 thermal images collected in the office space with added people locations. Moreover, the tiny encoder-decoder neural network was implemented and benchmarked to demonstrate dataset's feasibility. The performance tests have shown that the algorithm based on low-resolution input is able to provide accurate density estimation of people's locations. Furthermore, the method can be used on low-cost, resource-constrained edge devices. Although the Raspberry Pi is able to infer the model, the computing accelerators achieve better performance with only a slight increase in power consumption. The obtained measures indicate that in applications requiring low latency the best results are achieved with the Coral USB Accelerator. On the other hand, if the metrics are as crucial as inference time, the Intel Neural Compute Stick 2 should be considered. The performed tests confirm the usefulness of the dataset and edge AI hardware accelerators in IoT solutions. The Thermo Presence dataset is available in the project's repository at `https://github.com/PUTvision/thermo-presence`.

References

1. Abedi, M., Jazizadeh, F.: Deep-learning for occupancy detection using doppler radar and infrared thermal array sensors. In: Proceedings of the International Symposium on Automation and Robotics in Construction (IAARC). pp. 1098–1105 (2019). https://doi.org/10.22260/ISARC2019/0146
2. Beltran, E., Cerpa: Thermosense: Occupancy thermal based sensing for hvac control. In: In Proceedings of the 5th ACM Workshop on Embedded Systems for Energy-Efficient Buildings. pp. 1–8 (2013). https://doi.org/10.1145/2528282.2528301
3. Kraft, M., Aszkowski, P., Pieczyński, D., Fularz, M.: Low-cost thermal camera-based counting occupancy meter facilitating energy saving in smart buildings. Energies **14**(15) (2021). https://doi.org/10.3390/en14154542
4. Metwaly, A., Queralta, J.P., Sarker, V.K., Gia, T.N., Nasir, O., Westerlund, T.: Edge computing with embedded ai: Thermal image analysis for occupancy estimation in intelligent buildings. In: Proceedings of the INTelligent Embedded Systems Architectures and Applications Workshop 2019. pp. 1–6 (2019). https://doi.org/10.1145/3372394.3372397
5. Ronneberger, O., Fischer, P., Brox, T.: U-net: Convolutional networks for biomedical image segmentation. In: International Conference on Medical image computing and computer-assisted intervention. pp. 234–241. Springer (2015). https://doi.org/10.1007/978-3-319-24574-4$_2$8