
Datasheets for Machine Learning Sensors

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Abstract

Machine learning (ML) sensors offer a new paradigm for sensing that enables intelligence at the edge while empowering end-users with greater control of their data. As these ML sensors play a crucial role in the development of intelligent devices, clear documentation of their specifications, functionalities, and limitations is pivotal. This paper introduces a standard datasheet template for ML sensors and discusses its essential components including: the system’s hardware, ML model and dataset attributes, end-to-end performance metrics, and environmental impact. We provide an example datasheet for our own ML sensor and discuss each section in detail. We highlight how these datasheets can facilitate better understanding and utilization of sensor data in ML applications, and we provide objective measures upon which system performance can be evaluated and compared. Together, ML sensors and their datasheets provide greater privacy, security, transparency, explainability, auditability, and user-friendliness for ML-enabled embedded systems. We conclude by emphasizing the need for standardization of datasheets across the broader ML community to ensure the responsible and effective use of sensor data.

1 Introduction

The recent emergence of tiny machine learning (TinyML), a branch of ML dedicated to ultra-low power devices, has opened the door to a myriad of new possibilities for intelligent sensing at the edge by leveraging embedded systems [1, 2]. TinyML enables resource-constrained devices to perform complex computations with low latency and minimal energy consumption, making it particularly suitable for applications such as the Internet of Things (IoT), wearables, and smart sensors. However, integrating TinyML models into physical sensor systems can be complex, often requiring a deep understanding of ML algorithms and embedded systems. This knowledge barrier can hinder the widespread adoption of on-device intelligence. To address these challenges, the “ML sensor” has been proposed as an innovative solution that tightly couples the TinyML model with the physical sensor, effectively offloading the computational burden from the application processor [3]. This ML sensor architecture introduces useful layers of abstraction both at the hardware level and at the level of the full integrated device, creating a fully self-contained intelligent sensor module.

ML sensors, however, also present a new challenge: the lack of transparency [4, 5]. Unlike traditional sensors that come with datasheets providing hardware and operating characteristics, ML sensors lack such documentation. This absence hampers developers’ ability to assess sensor suitability and independently evaluate performance. To address this gap, ML sensors require a datasheet that not only includes traditional sensor specifications but also captures ML model characteristics, dataset details, and other important considerations such as environmental impact and end-to-end performance. With such a datasheet, users can easily determine whether an ML sensor is suitable for their application.

In this paper, we present the first ML sensor datasheet, developed as a collaboration between academia and industry, through the lens of a case study in person detection using two different sensors. Our template datasheet enables an ML sensor to offer transparency, auditability, and user-friendliness to system integrators and developers, simplifying, robustifying, and securing the deployment of TinyML into production embedded systems and applications. Furthermore, this approach allows developers to focus on designing and optimizing models without the need for extensive hardware expertise, thereby fostering rapid innovation and application of these new emerging technologies.

2 Background and Related Work

Historically, datasheets have been instrumental in detailing the physical attributes of hardware, including sensors. These documents outline features like power consumption, operating temperature, and application-specific parameters such as detection limits and measurement frequency. This information is critical for developers to ascertain sensor suitability for their specific applications and serves as a reference for quality assurance, especially in performance-critical workflows.

The concept of a datasheet has been extended to other domains, including ML. Recent research underscores the importance of thorough documentation for ML datasets, covering data collection, cleaning, labeling, and intended use [6, 7, 8]. While these studies targeted specific datasets, datasheets for datasets was proposed as a more general framework for documenting dataset characteristics [9]. The data nutrition label offers a similar diagnostic framework presenting a standardized view of a dataset’s important attributes [10, 11]. IBM has also introduced the idea of factsheets to document various features of ML services in order to bolster trust [12]. Beyond datasets, short documents accompanying trained ML models, known as model cards, have been proposed to provide benchmarked evaluations under diverse conditions relevant to intended application domains [13]. Efforts have also been made to include relevant privacy and security information to IoT devices [14, 15]. More recently, efforts have been made to characterize operational and embodied emissions of hardware devices, including TinyML, to help quantify their environmental impact in domains such as water usage, carbon emissions, and eutrophication potential [16, 17]. The growing trends in ML documentation and the increasing use of ML have highlighted the need for ethical considerations [18]. The trend towards responsible innovation reinforces the importance of transparency, auditability, accountability, and socially responsible practices for developers creating devices that may pervade society at scale [19].

Table 1 compares these prior datasheet works to the proposed ML sensor datasheet. Unlike prior works, ML sensors uniquely encompass integrated hardware, software, and machine learning elements, and as such an ML sensor amalgamates diverse concepts. Therefore, our work on datasheets for ML sensors builds on prior developments, asserting the need to augment a traditional sensor datasheet with vital ML elements (i.e., model, dataset) into a comprehensive datasheet. The subsequent sections outline our datasheet using a new commercial and open source sensor we developed.

Table 1: Comparison of ML sensor datasheets with other datasheet types.

Datasheets ↓	Env. Impact	Dataset	Model	Hardware	End-to-End	Privacy & Security
ML Sensors (our work)	Y	Y	Y	Y	Y	Y
Model Cards [13]	N	N	Y	N	N	N
Traditional Sensor Datasheet	N	N	N	Y	Y	N
Data Nutrition Label [10, 11]	N	Y	N	N	N	N
Datasheets for Datasets [9]	N	Y	N	N	N	N
IoT Security/Privacy Label [14, 15]	N	N	N	N	N	Y

3 ML Sensors

3.1 Paradigm

An ML sensor is a self-contained system that utilizes on-device machine learning to extract useful information by observing some complex set of phenomena in the physical world and reporting it through a simple interface to a wider system. The features of an ML sensor deviate from those of traditional on-device applications. As Figure 1a shows, rather than transmitting data to an application

processor, the processing occurs directly within the sensor itself. This approach prioritizes data locality, which brings about enhanced privacy and security as raw data is never transmitted. Only the summarized essential traits of the data that are extracted by an on-sensor ML model are conveyed off-sensor. This distinctive attribute signifies a fundamental shift in data handling, which makes ML sensors a significant evolution in sensor technology. Consequently, ML sensors like our own sensor designed for person detection—the process of identifying humans within images, typically via ML algorithms—as demonstrated in Figure 1b, are starting to become commercially available.

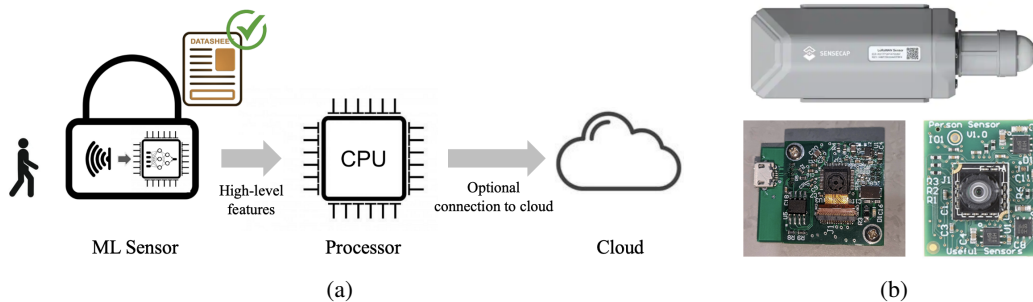


Figure 1: (a) The ML sensor paradigm. (b) Examples of existing ML sensors; *(top)* Seed Studio’s SenseCAP LoRaWAN sensor [20], *(bottom left)* our own person detection sensor whose design is publicly accessible, and *(bottom right)*, Useful Sensor’s person sensor [21]. We will be using our person detection sensor as the prime example for how we developed the ML sensor datasheet.

ML sensors present unique challenges due to their distinct architecture. Being devices that execute processing on the sensor itself, they demand an intricate balance of processing power, data handling, and privacy concerns. In traditional models, sensors and processors are distinct components, which allows for the division of labor. The sensor is primarily focused on data acquisition, while the processor handles the data processing. However, in the case of ML sensors, these roles are merged, putting a considerable load on the sensor. Another challenge is that of computational resource allocation. Sensors must be lightweight and energy-efficient while also being capable of deploying complex ML algorithms. Ensuring that an ML sensor has the requisite processing power without overwhelming its physical constraints is a significant design hurdle.

Data privacy and security also present unique challenges. While ML sensors provide enhanced privacy due to on-device processing, they also need to ensure data security at the sensor level. This might include secure execution of ML models and secure transmission of processed data. Furthermore, implementing ML at the sensor level requires the development of models small enough to be deployed on the sensor, but still complex enough to accurately process the data they’re designed to interpret. Designing these efficient yet effective models remains challenging. Finally, as the sensor needs to adapt to changes in the environment through ML, there is the challenge of continuous learning and model updates. Ensuring the ML sensor can handle this while upholding privacy and security assurances, as well as without increased power consumption or latency, is an area of ongoing research.

3.2 Motivation for a Datasheet

Figure 1b shows examples of existing ML sensors that can be used for person detection. These sensors can determine whether a person is present within view of the on-device camera. Such ML-enabled devices typically come with hardware specifications and information on utilizing the sensor’s capabilities, but often have limited information on (1) what data the on-device models are trained on, (2) the architecture of the model and how it performs on various related benchmarks, (3) environmental impact, (4) how the device performs in response to changing environmental parameters anticipated during deployment, and (5) information related to privacy, security, and compliance.

To enhance the comprehensibility and transparency of ML sensors, we must capture this comprehensive information to provide a well-rounded understanding of their functions, behavior, and potential impacts. Firstly, we need to know the specifics of the datasets used to train the on-device models. This includes information on the data’s origin, the diversity of scenarios it encompasses, and how representative it is of real-world situations that the sensors are likely to encounter. Secondly, details about the model’s architecture and performance benchmarks are crucial. We should understand the

type of model used, its complexity, how it has been trained, and its performance metrics on different benchmarks or real-world test scenarios. The environmental impact of the sensors should also be documented, detailing their energy consumption, carbon footprint, and waste production, among other things. Fourthly, detailed information on the device’s performance in a dynamic end-to-end environment is essential. This includes how the sensor reacts to varying environmental parameters, such as light conditions and distance from the device. Finally, information pertaining to privacy, security, and compliance is paramount. We need to understand if and how data is stored and transmitted, what privacy measures are in place, how user data is protected, and whether the device complies with the relevant regulations and standards. In essence, complete information about all these aspects will make the ML sensors more understandable, manageable, and reliable in their application.

4 The ML Sensor Datasheet

A datasheet is a document detailing the features and characteristics of a product. Datasheets are a standard component of commercially available sensors and enable users to evaluate device suitability. In this section, and as diagrammed in Figure 2, we present what we believe should be the sections of an ML sensor datasheet. Our format captures both traditional sensor components, as well as machine learning components, environmental impact, responsible AI analysis, and end-to-end system performance metrics. This datasheet format is designed to capture both best-practices from the literature, as well as our experience developing an open-source, commercially-relevant ML sensor.

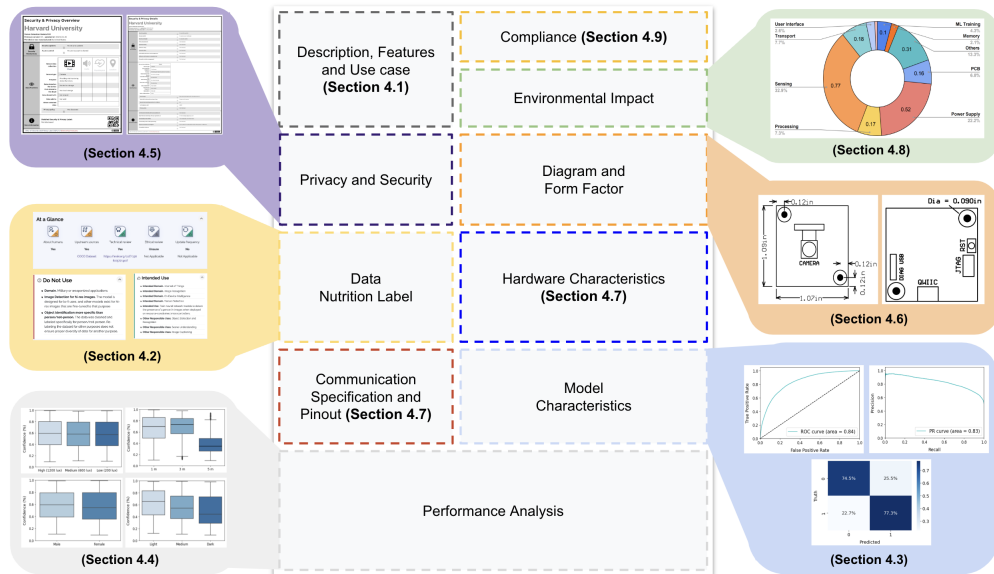


Figure 2: Schematic of the proposed ML sensor datasheet encompassing 10 distinct sections that combine traditional sensor datasheet components with machine learning components, environmental impact and responsible AI analysis, and end-to-end system performance metrics.

4.1 Description

What are high-level characteristics of the sensor? The description section of the ML sensor datasheet provides an introduction to the device for both technical and non-technical audiences. On the technical side, it includes intricate details about the device’s specifications, architecture, and operational principles. For non-technical readers, it offers a more accessible description, explaining the sensor’s purpose and function in plain language. This section also highlights key features of the ML sensor, such as high sensitivity, low power consumption, robust data processing capabilities, and its adaptability to various environmental conditions. Additionally, it presents a list of common applications where the sensor could be beneficial, such as predictive maintenance in industrial settings, environmental monitoring, healthcare diagnostics, autonomous vehicles, and smart home systems. In the context of our person detection sensor (Figure 1b), the description would be “a device that predicts whether an individual is present in the view of the camera and outputs a corresponding signal response.”

4.2 Dataset Nutrition Label

What data is the model trained on? To evaluate the dataset used in training the on-device model, we utilize the second-generation Dataset Nutrition Label [11, 10]. This label communicates high-level dataset information to end-users, including (1) the sources of the dataset (i.e., governmental, commercial, academic), (2) licensing details of the dataset, (3) data modality, and (4) context-specific information (e.g., human-labeled, contains information about human individuals), amongst other information. This label promotes transparency and accountability by providing detailed information about the context, content, and quality of dataset(s) used in training the ML model. As such, it fosters responsible development and deployment of models by making it easier for developers, researchers, and stakeholders to assess data quality and potential biases such as sampling, measurement, and label bias [22, 23]. The data nutrition label for the person detection sensor shown in Figure 1b highlights that the dataset, the Visual Wake Words dataset [24], is from an upstream source (MS-COCO [25]), contains information about humans obtained without consent, and that the dataset is not currently managed or updated by any entity. The label for our devices can be found in Appendix B.

4.3 Model Characteristics

What are the characteristics of the trained model? This section of the datasheet provides insights into the specific ML model operating within the sensor. This includes important details such as the type of the ML model used, the size of the model in terms of parameters, the type and size of input data it can process, and the nature of output it generates. This section also discusses the model’s performance metrics, such as accuracy, precision, recall, F1 score, or receiver operating characteristics (ROC), measured on a relevant validation dataset. It may also address the model’s robustness to variations in input data, its sensitivity to noise, and its generalization capabilities. This section is vital for users to understand the underlying technology of the sensor, its computational requirements, its performance under different operating conditions, and ultimately, its suitability for their specific use cases. Figure 3 shows some example model characteristics of the ML sensor running a MobileNetV1 architecture [26] trained for person detection. The ROC curve shows that the optimal threshold value lies around 0.52 to balance false positives and false negatives, which were valued equally. The confusion matrix shows the accuracy of the model on the test set using this specific threshold value.

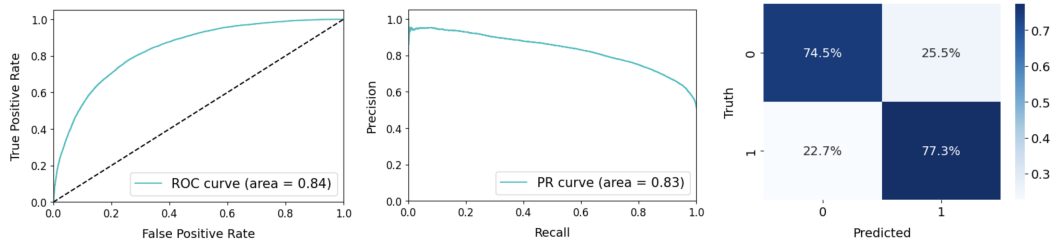


Figure 3: ROC curve (*left*), precision-recall curve (*center*), and confusion matrix (*right*) for the person detection ML sensor evaluated on a test set. The confusion matrix was calculated with the optimal threshold value of 0.52.

4.4 Sensor Performance Analysis

How does the device perform as a whole with changing environmental parameters? The end-to-end performance analysis section of the datasheet provides an encompassing evaluation of the sensor’s performance from data acquisition to data processing and output generation. This holistic performance analysis may include metrics such as data collection rate, latency, power consumption, and accuracy of the sensor’s outputs under a range of conditions. Additionally, it highlights the performance of the ML model when deployed on the sensor hardware, taking into account aspects such as data preprocessing, inference speed, and model accuracy. The analysis could also encompass how the sensor’s performance scales with changes in workload or environmental conditions. This section is crucial as it helps potential users understand not only the isolated performance of the sensor’s components but also how they work together to provide a coherent service. This understanding is vital when integrating the sensor into larger systems or evaluating its fit for particular use-cases.

We present an exemplary case study of end-to-end performance analysis on our open-source person detection sensor in Figure 4, using data from three sensors to capture device variability. For a detailed description of the experimental study please see Appendix A. In particular, we assess our device’s performance under a set of different lighting conditions and distances on a diverse group of volunteers with a range of skin tones and genders. These analysis provide examples of both device efficiency under changing environmental conditions, a common type of analysis on standard sensor datasheets, as well as possible demographic biases embedded within the ML model. Figure 4a shows that lighting conditions had little impact on performance, likely as a result of the high contrast testing environment, while Figure 4b shows that performance degraded sharply when distance increased from 3-5 meters. Figures 4c, and 4d show that the model performed slightly better on men than on women and demonstrated a skin tone bias which favored lighter skin tones, warning of potential biases in the open-source pipeline used to develop the particular model on the device. We note that in particular, the diversity of clothing worn by study participants was not captured in this data and may have had a significant effect on our results.

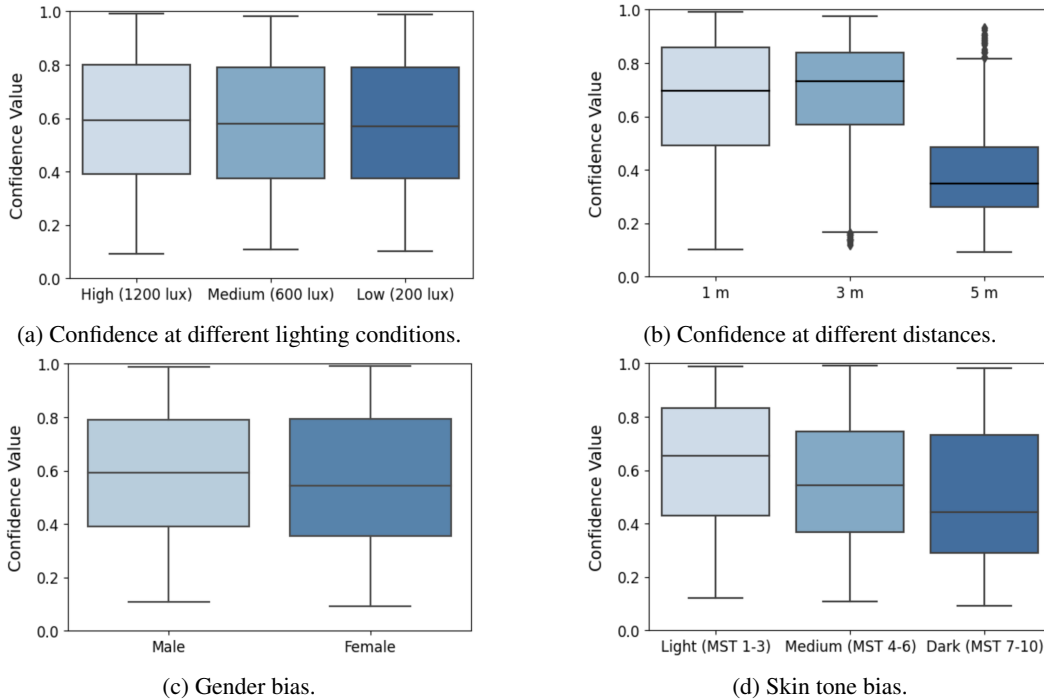


Figure 4: End-to-end performance analysis of the ML sensor tested on 38 volunteers under controlled laboratory conditions. Skin tone was estimated using the Monk Skin Tone (MST) Scale [27].

4.5 Security and Privacy

What security and privacy features does the ML sensor have? The IoT security and privacy label is aimed at enhancing consumer awareness and facilitating informed decision-making when purchasing smart devices [14]. This label aims to promote transparency and empower consumers, allowing them to make well-informed choices in an increasingly connected world. The label is structured in two distinct layers: a primary layer, which conveys essential privacy and security information in a concise and easily digestible manner, and a secondary layer, which delves into further detail for experts and more technically inclined users. The primary layer, intended for display on product packaging or online shopping platforms, highlights key aspects such as data collection practices, automatic security updates, firmware versions, and the device’s ability to operate without internet connectivity. Meanwhile, the secondary layer can be accessed through a URL or QR code and provides in-depth information on privacy and security protocols, offering valuable insights for those seeking a deeper understanding of a device’s potential risks and safeguards. For our ML sensor, the IoT security and privacy label shows that there is only a camera on the device collecting data continuously, but this data is not stored or transmitted off-device. The label for our device can be found in Appendix B.

4.6 Device Diagrams

What does the device size, shape, and layout look like? The device diagram section of the ML sensor datasheet provides visual depictions and physical dimensions of the device. It includes detailed diagrams that illustrate the sensor’s internal components and their interconnections, offering insights into the design and operation of the sensor. For non-technical audiences, these diagrams can provide a more intuitive understanding of the device, beyond what text descriptions can offer. These diagrams include form factor information which describes the physical shape, size, and layout of the sensor, since this data is crucial in planning the sensor’s integration into various systems and devices. These details for the person detector are shown in Figure 5, with the full datasheet provided in Appendix B.

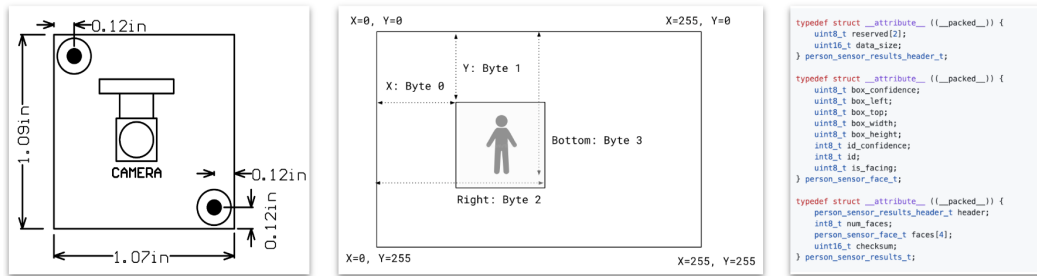


Figure 5: (left) Device diagram of person detection ML sensor, (middle) standard for data communication, and (right) schema for communication of data off-sensor.

4.7 Hardware Characteristics

How do I use, power, and interface with the device? This section of the datasheet provides an overview of the physical and functional attributes of the device. It contains specifics about the sensor’s integral hardware components, including the processor type, memory capacity, power requirements, and durability under different environmental conditions. In addition, it includes detailed information about the communication protocols supported by the sensor, such as Wi-Fi, Bluetooth, or cellular connectivity, along with data transfer rates. This data is crucial in determining the sensor’s compatibility with existing hardware infrastructure. For instance, it can inform whether the sensor can efficiently transmit data over a specific network or whether it can endure specific environmental conditions. Figure 5 (left) shows our ML sensor with a square form factor and dimensions 27.2mm × 27.7 mm. It employs the industry-standard Inter-Integrated Circuit (I²C) interface via a Qwiic connector [28], allowing a data transfer rate of up to 100 kB/s. Figure 5 (middle) and (right) show the data standard and open-source schema we developed for communication [29]. The sensor communicates through a single byte with values from 0 to 255. The device can accept voltages in the range 3.5-5.5 V with a 40 mA operating current.

4.8 Environmental Impact

How does the device affect the environment during its lifecycle? There are currently around 15 billion IoT devices with projections of billions more to come each year [30]. However, embedding smart computing into everyday objects has looming environmental consequences through increased electronic waste [31]. With the added widespread deployment of smart sensors, it is essential to consider and be conscious of the environmental impact such ubiquitous computing may have. Therefore, another component we advocate to be included in the datasheet is an “environmental impact” section that outlines the device’s footprint. As such, we generated a sample of what this section might look like as part of the datasheet for our sensor specifically.

We captured the carbon footprint (CO₂-eq.) of our ML sensor using the methodology and TinyML Footprint Calculator from Prakash et al. [17]. The calculator has fields for processing, sensing, power supply, memory, PCB, and more, enabling us to input specifications from our bill of materials. Furthermore, in addition to the bill of materials, we capture the carbon footprint for the ML sensor’s model training, transport, and three-year use. The total carbon footprint, including embodied and operational footprint, of our ML Sensor is approximately 2.34 kg CO₂-eq. Figure 6 shows that the majority of the footprint can be attributed to the power supply and camera sensor. We note that other

important environmental impact indicators, such as freshwater eutrophication, should ideally also be included in future datasheets. However, this would require us to broader information about upstream products and manufacturing processes which are not freely available. To address this, compliance and certification mechanisms could provide an avenue for incorporating a broader range of factors into the environmental impact analysis.

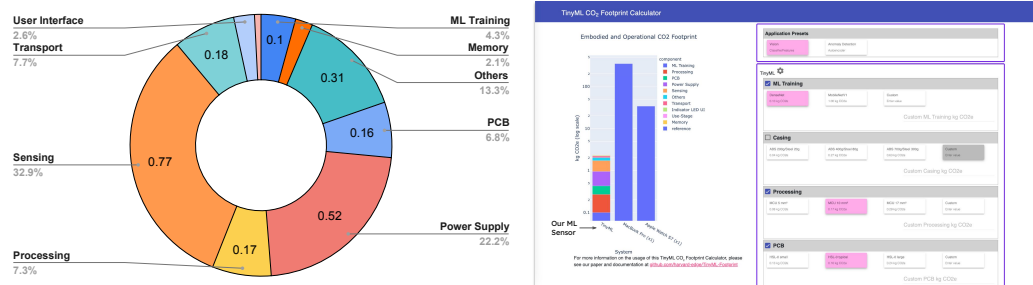


Figure 6: Carbon footprint breakdown by component of our ML sensor (left). Units are in kg CO₂-eq. Using the TinyML Footprint Calculator from Prakash et al. [17](right), we compute the footprint including the environmental cost for sensor transportation and ML model training. The total carbon footprint, including embodied and operational footprint, is approximately 2.34 kg CO₂-eq.

4.9 Compliance and Certification

Which international regulations and industry standards does the device conform to? The compliance and certification section of the ML sensor datasheet catalogs the sensor’s alignment with various regulatory and industry standards. It lists the certifications the sensor has achieved, signifying thorough testing and validation by recognized certification bodies. These may encompass international data privacy regulations like GDPR [32], radio frequency usage guidelines like FCC regulations, or industry-specific requirements like HIPAA [33] or FDA standards in healthcare. This section could also showcase adherence to voluntary industry-specific best practices, such as ISO 26262 standard [34] for autonomous vehicles or IEC 61508 [35] for industrial automation systems.

Beyond simply listing certifications, this section offers an in-depth understanding of the sensor’s capabilities and boundaries, denoting aspects like its Ingress Protection rating or compatibility with certain environmental conditions. Compliance with these standards vouches for the sensor’s reliability, safety, and overall quality, instilling confidence in developers and end-users about its dependable operation. It communicates that the sensor has been meticulously designed and manufactured to meet or surpass specific standards, providing assurance in its performance and longevity. This section serves as a key reference for users evaluating the sensor’s suitability for their needs. While our own ML sensor has not undergone the process to obtain specific certifications or verification of compliance to standards, this would be appropriate for commercial devices. Currently, no certification body or defined standards exists specifically for ML sensors, but a mechanism could be implemented that is tied to existing non-profit entities focused in the area (e.g., the TinyML Foundation).

5 Discussion

Our datasheet template finds relevance in numerous practical applications, including predictive maintenance in industrial settings [36], environmental monitoring [37, 38], healthcare diagnostics [39], autonomous vehicles [40], and smart homes [41]. By detailing the hardware characteristics and conformity with industry and regulatory standards, the datasheet provides developers and users with a dependable tool to assess sensor suitability for their specific use-cases. However, we acknowledge that there are limitations to our current approach. First, while we have provided a template based on commercially relevant sensors, the versatility of the template across various types of sensors and applications may still need further testing. Moreover, the datasheet heavily relies on the accuracy and honesty of the information provided by the manufacturers or developers. Hence, there is a potential risk of misinformation or misinterpretation without the implementation of oversight mechanisms.

Finally, despite our focus on improving transparency into the privacy and security implications of ML sensors, fool-proof methods to eliminate harmful applications do not exist, necessitating careful consideration when designing these devices. To facilitate **responsible innovation in ML sensors**, several underlying principles should be considered:

- **Minimize Risks.** Limit factors like connectivity and updatability to mitigate potential risks, while acknowledging the impossibility of eliminating all possible harmful applications.
- **Address Ethical Challenges.** Recognize that traditional ML ethical concerns persist in the ML sensor paradigm, with additional considerations needed for running ML locally.
- **Prioritize Privacy and Security.** Implement built-in safeguards against accessing personal data and ensure secure hardware to prevent potential misuse by malicious actors.
- **Encourage Transparency.** Require publicly available datasheets detailing essential properties of ML sensors, allowing product integrators and end-users to be aware of limitations.
- **Establish Third-Party Audits and Certifications.** Collaborate with organizations to develop recognized standards, certification processes, and third-party auditing mechanisms.

In looking towards the future, our datasheet template opens up numerous avenues for further exploration and improvement. For example, in the field of healthcare, refining the template to accommodate the unique needs and regulations for medical devices could be incredibly valuable. This could involve detailing the sensor’s biocompatibility, sterilization procedures, or patient data privacy protocols. Similarly, for industrial applications such as predictive maintenance or process control, future research could focus on expanding the datasheet’s sections on durability, reliability under extreme conditions, or integration with industrial control systems. In the realm of autonomous vehicles, the datasheet could be optimized to elaborate on aspects such as real-time performance, resilience to hacking, or interoperability with other vehicle components. For consumer applications like smart home systems, the datasheet could be further simplified and made more accessible to non-technical users, while retaining key information about data privacy, power consumption, or compatibility with other smart devices. By addressing these specific use-cases and their unique requirements, we could significantly enhance the datasheet’s effectiveness and applicability, ensuring it remains a robust tool for developers, integrators, and end-users across diverse sectors.

6 Statement of Ethics

Our datasheets were developed in accordance to stringent ethical standards, with careful data collection and processing in line with legal and ethical guidelines. Throughout the study (i.e., previous sections) we have aimed to demonstrate unbiased data representation and transparency regarding sensor attributes. Aware of potential dual-use implications, we have proposed a set of principles to foster responsible innovation of ML sensors and their datasheets to help mitigate possible misuse.

7 Conclusion

The advent of ML sensors has brought forward the necessity for transparent, comprehensive, and standard documentation of edge ML systems. This paper has introduced a new datasheet template tailored for ML sensors, synthesizing essential aspects of traditional hardware datasheets with key elements of machine learning and responsible AI. Our template provides a detailed account of ML sensor attributes such as hardware, ML model, dataset, end-to-end performance, and environmental impact. These datasheets are designed to empower end-users and developers with a thorough understanding of ML sensors’ capabilities and limitations, thereby fostering responsible and effective use. Two real-world sensors were used to illustrate the practical application of these datasheets, highlighting their potential to enhance transparency, auditability, and user-friendliness in ML-enabled systems. Moving forward, it is crucial for the ML community to recognize the value of these datasheets and work towards their widespread adoption and standardization. We hope that this research can catalyze further discussion and exploration in this critical area of ML technology.

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Appendix

A. Experimental Study



Figure A.1: This figure presents a dual-view illustration. The left panel shows a wall-mounted sensor assembly, consisting of sensors developed by Harvard on the left side and those provided by Useful Sensors on the right. The right panel depicts the experimental environment where study participants stood in front of the sensor setup. Distances from the sensor setup (1m, 3m, and 5m) are marked on the floor for participant positioning.

The end-to-end performance of the person detection sensor model was tested through an experimental study conducted in the Science and Engineering Complex (SEC) at Harvard University. The study involved XX participants and evaluated the accuracy of the model under different lighting conditions using three identical sensors.

The study room measured 25 x 31 x 10 ft and contained 32 ceiling lights that were uniformly distributed in a 4 x 8 grid. The lighting conditions were captured quantitatively for each participant using a Lux LCD Illuminance Meter (Precision Vision, Inc.) and a C-800-U Spectrometer (Sekonic Corporation).

The sensors were mounted on a wooden board affixed to the wall at a height of 1.5 m above the ground. The participants were evaluated at three different distances (1.5 m, 4.5 m, and 7.5 m) from the sensors under each lighting condition. The ambient lighting in the room was provided by artificial lights, and blackout curtains were used to block the ambient lighting from outside.

The lighting levels were controlled using a dimmer switch that had three levels of operation, with corresponding to 208 ± 31 , 584 ± 51 , and 1149 ± 59 lux, respectively. When the lights were turned off, the illuminance meter gave a reading of zero lux. When all the lights were turned on at full strength, the sensor gave an average reading of 1149 lux. The color temperature of the lighting was measured to be 5600 K, corresponding to white light. Colored tape was placed on the ground to demarcate the locations where participants should stand during the experiment (i.e., 1.5, 4.5, and 7.5 m from the sensor array).

Before entering the study environment, the participants were asked to provide their gender identity and evaluate their skin tone according to the Monk Skin Tone (MST) Scale to evaluate algorithmic bias. The study evaluated algorithmic bias by bucketing skin tone into three categories: light (MST 0-4), medium (MST 5-7), and dark (MST 8-10). At each location and lighting condition, ten readings were taken from each sensor and averaged.

Participants were recruited using flyers, and those interested filled out a Study Interest Form. Upon arrival, participants signed a Consent Form indicating their willingness to participate in the study. The accuracy of the model is provided in the following graphs as a function of lighting condition, distance, gender identity, and skin tone. Overall, 63.2% of the participants were male, and 36.8% were female; the percentage of participants corresponding to each skin tone group was: 47.4% light, 39.4% medium, and 13.2% dark.

B. Example Data Sheet - Person Detection Sensor

OVERVIEW.....	15
Compliance and Certifications.....	15
Description.....	15
Features.....	15
Use Cases.....	15
MODEL CHARACTERISTICS.....	16
Software Flow Diagram.....	17
Dataset Nutrition Label.....	18
IoT Security and Privacy Label.....	21
Machine Learning Model Specification.....	23
Performance Analysis.....	25
Environmental Sensitivity.....	26
Demographic biases.....	26
HARDWARE CHARACTERISTICS.....	27
Hardware Details.....	28
Device Diagrams.....	29
Bill of Materials.....	30
Environmental Impact.....	31
Acronyms.....	32
Glossary.....	33

OVERVIEW

PA1 Person Detection Module



HARVARD

**School of Engineering
and Applied Sciences**

Compliance and Certifications

The person detection sensor complies with essential industry standards and regulations, including RoHS for environmental safety and GDPR for protecting individual privacy. As of the time of writing, the sensor does not have any certifications from third-party organizations.

Description

The PA1 Person Detection Module is a cost-effective device that uses a machine learning (ML) algorithm to detect the presence of a person within its range. The sensor is equipped with cameras and sensors that capture images and data from the surrounding environment. These images and data are then processed by the on-device ML algorithm to identify people. When a person is detected, the sensor sends an alert or trigger to connected devices or systems, allowing them to perform specific actions such as activating security cameras, turning on lights, or opening doors. The person detection sensor is ideal for use in security, home automation, and other applications that require quick and accurate detection of people.

The sensor has a small form factor and utilizes a monochrome camera with a field of view of 320 x 320 (QVGA). The sensor is equipped with an onboard 3.3V regulator, which enables it to operate with an input voltage range of 3.5V - 5.5V when enabled, or 3.0V - 3.6V when disabled. The typical operating current for the sensor is 40 mA. The sensor communicates via I2C/Qwiic mode, conforming to SparkFun Qwiic electrical/mechanical specifications, and has a maximum cable length of 1 m. The sensor has a maximum data rate of 100 kb/s and a wide sensitivity coverage of 0.1 - 10 klux.

Features

- Real-time person detection with on-device ML
- Indoor and outdoor use
- Low power consumption
- Onboard camera
- Small form factor: 10 x 10 x 2 mm
- I2C serial communication
- Wide sensitivity coverage: 0.1 - 10 klux

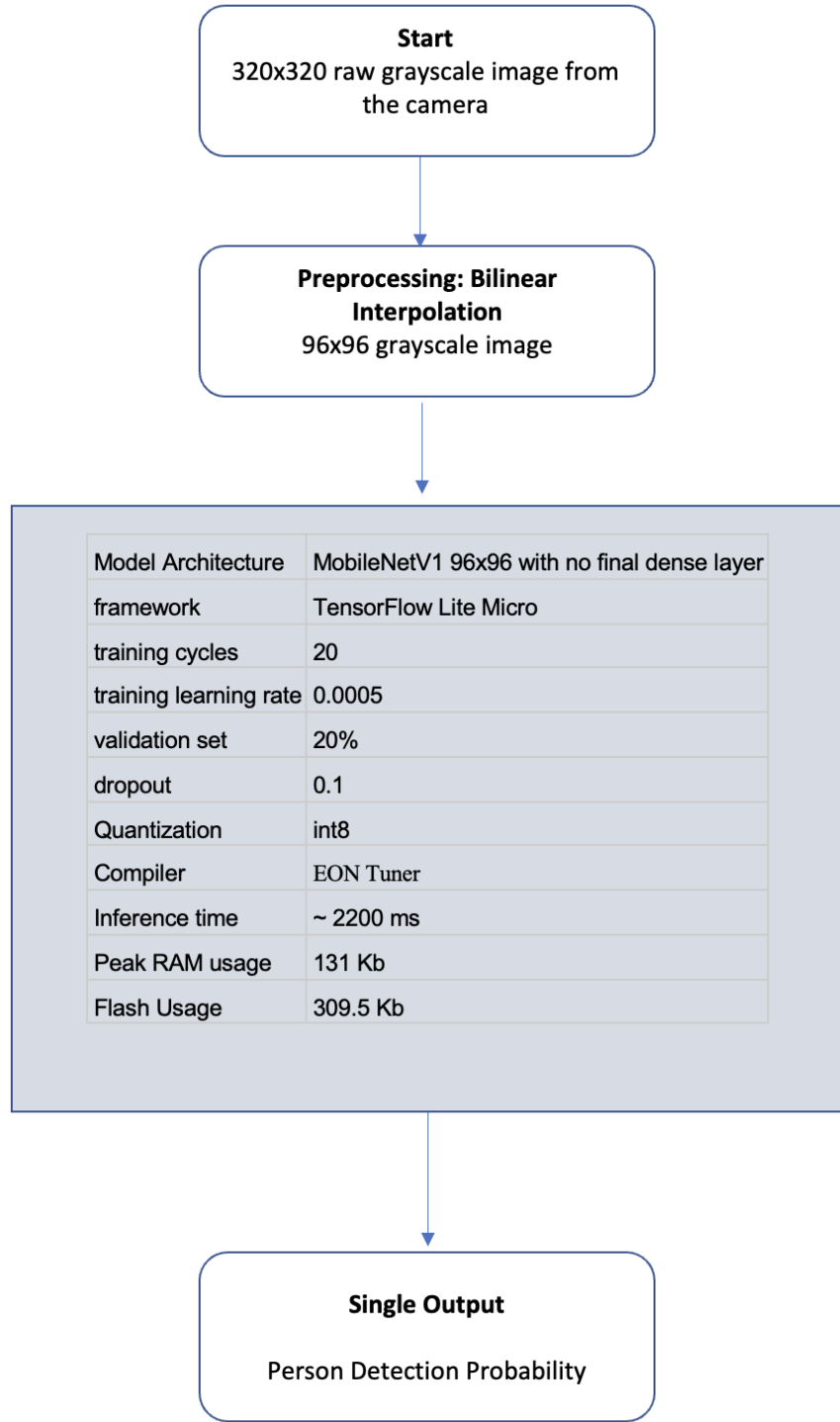
Use Cases

- Security
- Home automation
- Consumer appliances

MODEL CHARACTERISTICS

Software Flow Diagram

Grayscale images (320x320) are collected and resized to 96x96 via bilinear interpolation. Images are fed into a MobileNetV1 architecture trained and optimized through Edge Impulse. The output probability is communicated via Qwiic interface to the application processor.



Dataset Nutrition Label

At a Glance



About humans

Yes



Upstream sources

Yes

COCO Dataset



Technical review

Yes

<https://arxiv.org/pdf/1906.05721.pdf>



Ethical review

Unsure

Not Applicable



Update frequency

No

Not Applicable

Do Not Use

- **Domain.** Military or weaponized applications
- **Image Detection for hi-res images.** The model is designed for lo-fi uses, and other models exist for hi-res images that are fine-tuned to that purpose
- **Object Identification more specific than person/not-person.** The data was cleaned and labeled specifically for person/not-person. Re-labeling the dataset for other purposes does not ensure proper diversity of data for another purpose.

Collection process

The MS-COCO dataset was collected through sourcing diverse images from Flickr and using Amazon Mechanical Turk for human annotators to draw polygons around object instances and provide descriptive captions for each image, followed by quality control measures to ensure annotation consistency. The Visual Wake Words dataset was derived from this by selecting the subject of images containing "person" and "non-person" labels.

Intended Use

- **Intended Domain.** Internet of Things
- **Intended Domain.** Image Recognition
- **Intended Domain.** On-Device Intelligence
- **Intended Domain.** Person Detection
- **Intended Use.** Train neural network models to detect the presence of a person in images when deployed on resource-constrained microcontrollers.
- **Other Responsible Uses.** Object Detection and Recognition
- **Other Responsible Uses.** Scene Understanding
- **Other Responsible Uses.** Image Captioning

🏠 General risks

Any additional risks?

Individual Information

yes

Consent

Consent was not given.

Generalized Inferences

The original source material, from COCO, is mainly made up of photographs from Flickr, and it's not clear to what extent the users of Flickr are representative of the population at large outside the U.S., for instance.

Generalized Inferences - Mitigation

Identifying a specific use case for models made using this dataset, creating a list of situations in which people would be found for that use case, and then reviewing the base dataset to ensure it has a diversity of images related to the situations you identify (this may be a somewhat manual process).

Sensitive Content

Not Applicable

Documented Known Issues

https://medium.com/@jamie_34747/how-i-found-nearly-300-000-errors-in-ms-coco-79d382edf22b

Other Known Issues

Some items in both the person and non-person categories are known to be mislabeled.



Number of issues

Risky	2
Safe	1
Unknown	4

📄 Feature selection

Which columns were chosen and why?

Cultural or Domain Assumptions

Proxy Characteristics

Planning Representation

Domain Knowledge

Some familiarity with the style of how images are labeled in the COCO datasets would be helpful



Number of issues

Risky	1
Safe	1
Unknown	2

🔍 Representation

Which rows were included and why?

Subpopulation Information

Not Applicable

Representation

Unknown

Individual Inferences

Decisions or predictions based on the dataset may not accurately account for individual variations, such as clothing and accessories worn by an individual, and could result in overgeneralized outcomes that don't consider unique circumstances or factors. Additionally, the data may include bias due to its data collection practices which may lead to unfair or discriminatory decisions.

Individual Inferences - Mitigation

Collection Representation

Other Representation Issues



Number of issues

Risky	1
Safe	0
Unknown	5

🔍 Data values

What values are in each column?

Collection and Labeling Protocols

The data was generalized from its original description to be that of a "person" or "not person", which required scraping of the original dataset based on search parameters entered by the authors of the dataset. The upstream dataset used Amazon Mechanical Turk workers to label pictures as well, on a custom interface created by the upstream dataset authors.

Data Imputation Protocols

Data Manipulation Protocols

Missing Data

The dataset is derived from MS-COCO and thus contains all items within that dataset that include person and non-person tags.

Raw Data



Number of issues

Risky	1
Safe	0
Unknown	4


IoT Security and Privacy Label


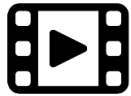



This device contains a camera that takes pictures at 1 s intervals. No other sensory data is collected. Raw data is contained solely within the ML module, with only high-level features transmitted to the main processor (i.e., no image data is accessible by the main processor). This module has no internet connectivity or data storage capacity outside the model and software.

Security & Privacy Overview



Harvard University


Person Detection Module PA1
 Firmware version: 0.1 - updated on: 2023-02-20
 The device was manufactured in: United States

 Security Mechanisms	Security updates No security updates
	Access control No user account is allowed

 Data Practices	 Visual	 Audio	 Physiological	 Location	
	Sensor data collection				
	Sensor type	Camera			
	Purpose	Providing and improving device functions			
	Data stored on the device	No device storage			
	Data stored in the cloud	No cloud storage			
	Data shared with	Not shared			
	Data sold to	Not sold			
Other collected data					

Privacy policy Not disclosed

 More Information	Detailed Security & Privacy Label: Not disclosed	
--	--	---

CMU IoT Security and Privacy Label CISPL 1.0 iotsecurityprivacy.org





Security & Privacy Details

Harvard University

Person Detection Module PA1

Firmware version: 0.1 - updated on: 2023-02-20

The device was manufactured in: United States

 <p>Security Mechanisms</p>	Security updates	No security updates																								
	Access control	No user account is allowed.																								
	Security oversight	No security audits																								
	Ports and protocols	Not disclosed																								
	Hardware safety	Not disclosed																								
	Software safety	Not disclosed																								
	Personal safety	Not disclosed																								
	Vulnerability disclosure and management	Not disclosed																								
	Software and hardware composition list	Not disclosed																								
	Encryption and key management	Not disclosed																								
 <p>Data Practices</p>	<table border="1"> <tr> <td>Sensor data collection</td> <td>Visual</td> </tr> <tr> <td>Sensor type</td> <td>Camera</td> </tr> <tr> <td>Data collection frequency</td> <td>Continuous</td> </tr> <tr> <td>Purpose</td> <td>Providing and improving device functions</td> </tr> <tr> <td>Data stored on the device</td> <td>No device storage</td> </tr> <tr> <td>Local data retention time</td> <td>No retention</td> </tr> <tr> <td>Data stored in the cloud</td> <td>No cloud storage</td> </tr> <tr> <td>Cloud data retention time</td> <td>No retention</td> </tr> <tr> <td>Data shared with</td> <td>Not shared</td> </tr> <tr> <td>Data sharing frequency</td> <td>Not shared</td> </tr> <tr> <td>Data sold to</td> <td>Not sold</td> </tr> <tr> <td>Other collected data</td> <td>None</td> </tr> </table>	Sensor data collection	Visual	Sensor type	Camera	Data collection frequency	Continuous	Purpose	Providing and improving device functions	Data stored on the device	No device storage	Local data retention time	No retention	Data stored in the cloud	No cloud storage	Cloud data retention time	No retention	Data shared with	Not shared	Data sharing frequency	Not shared	Data sold to	Not sold	Other collected data	None	
	Sensor data collection	Visual																								
	Sensor type	Camera																								
	Data collection frequency	Continuous																								
	Purpose	Providing and improving device functions																								
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	Local data retention time	No retention																								
	Data stored in the cloud	No cloud storage																								
	Cloud data retention time	No retention																								
	Data shared with	Not shared																								
Data sharing frequency	Not shared																									
Data sold to	Not sold																									
Other collected data	None																									
Data linkage	Data will not be linked with other data sources																									
What will be Inferred from User's Data	Presence of a human																									
Special data handling practices for children	No																									
In Compliance with	GDPR																									
Privacy policy	Not disclosed																									
 <p>More Information</p>	Call Harvard University with your questions at	Not disclosed																								
	Email Harvard University with your questions at	ml-sensors@googlegroups.com																								
	Functionality when offline	Full functionality on offline mode																								
	Functionality with no data processing	Not disclosed																								
	Physical actuations and triggers	Device performs customized actions when person is detected.																								
	Compatible platforms	Not disclosed																								

Machine Learning Model Specification

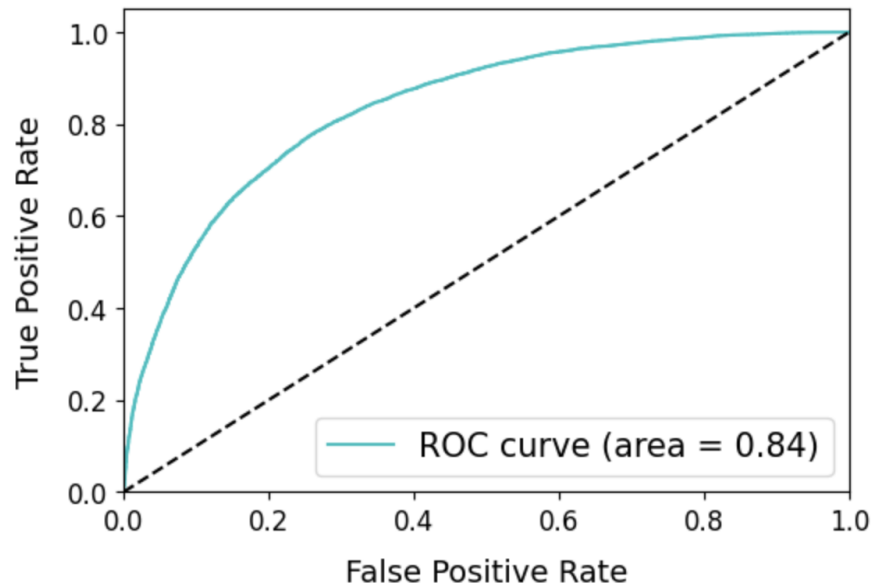
The person detection model was created using transfer learning with the [MobileNetV1](#) neural network (see architecture [here](#)) on Edge Impulse. The training and testing of the model were done using a subset of images from the [MS-COCO 2017 dataset](#), which is widely used for image recognition. Only images containing humans were selected from the dataset, totaling 109,604 images. The derived dataset is equivalent to the [Visual Wake Words dataset](#). A train/test split ratio of 0.8 was used.

The input to the model is a 96x96 raw image in 8-bit grayscale format, equivalent to 27648 features. The training process was carried out over 20 cycles with a learning rate of 0.0005 and a validation set of 20% on MobileNetV1 with a dropout of 0.1 and no final dense layer. The output layer of the model produces a two-class vector of results, indicating the probability of a person being present in the image. The unoptimized (float32) model has an accuracy of 76.3%, with a false positive (FP) and false negative (FN) rate of 20.7% and 26.8%, respectively. The model was quantized to int8 and deployed on Edge Impulse using the integrated EON-Compiler to produce a C++ library. The quantized model has an accuracy of 75.5%, with an FP and FN rate of 23.9% and 25.1%.

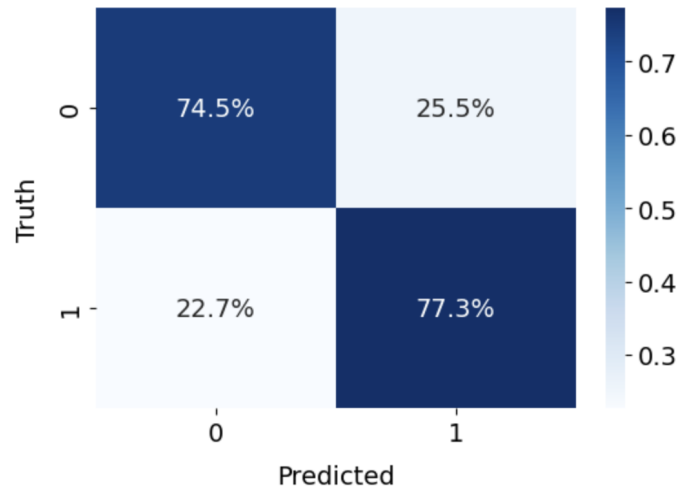
To enable live person detection, a set of image provision scripts was added to the software pipeline. The scripts continuously capture data from the onboard camera and pass it to the model in the appropriate scale and format. Using the Arm GNU Toolchain, the Pico-SDK, and the resulting C++ library, the model was built and compiled into a binary file that can be flashed to the ML board [See README/GitHub Repo]. The output of the model is an output vector consisting of a non-person score and a person score, which is communicated through a serial connection and can be viewed on a serial monitor.

Model workflow and characteristics can be viewed through the public Edge Impulse project version [here](#).

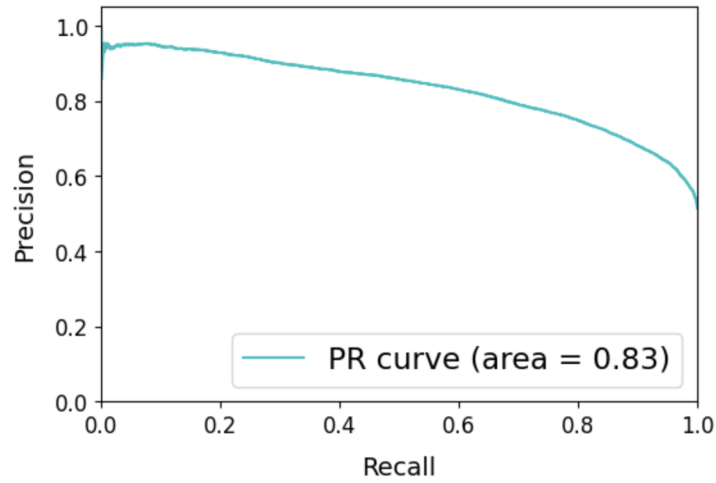
(a) Receiver Operating Characteristic Curve



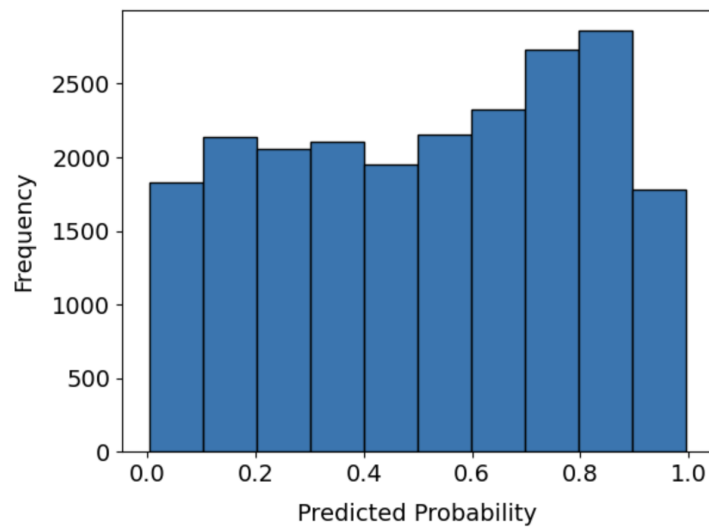
(b) Confusion Matrix



(c) Precision-Recall Curve



(d) Histogram of Predicted Probabilities



Performance Analysis

The end-to-end performance of the person detection sensor model was tested through an experimental study conducted in the Science and Engineering Complex (SEC) at Harvard University. The study involved 40 participants and evaluated the accuracy of the model under different lighting conditions using three identical sensors.

The study room measured 25 x 31 x 10 ft and contained 32 ceiling lights that were uniformly distributed in a 4 x 8 grid. The lighting conditions were captured quantitatively for each participant using a [Lux LCD Illuminance Meter](#) (Precision Vision, Inc.) and a [C-800-U Spectrometer](#) (Sekonic Corporation).

The sensors were mounted on a wooden board affixed to the wall at a height of 1.5 m above the ground. The participants were evaluated at three different distances (1.5 m, 4.5 m, and 7.5 m) from the sensors under each lighting condition. The ambient lighting in the room was provided by artificial lights, and blackout curtains were used to block the ambient lighting from outside.

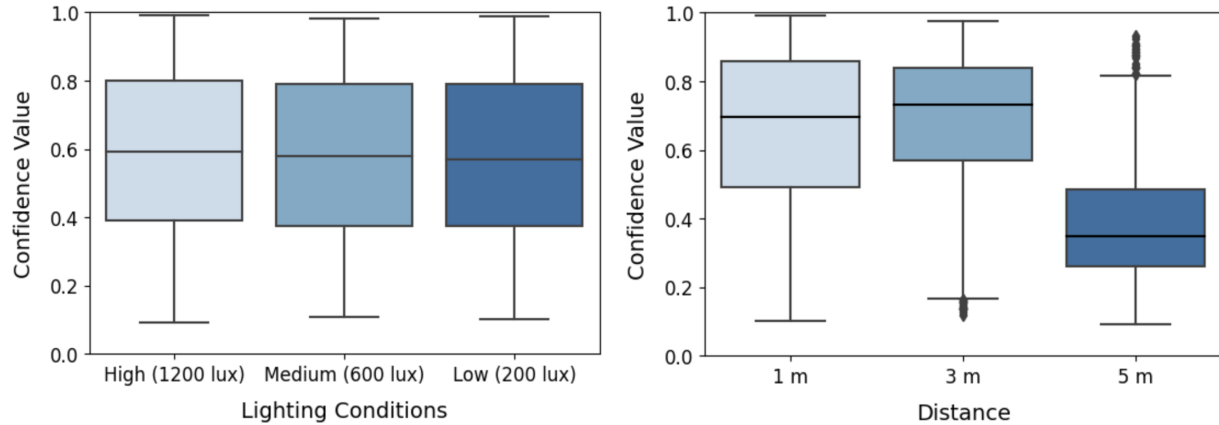
The lighting levels were controlled using a dimmer switch that had three levels of operation, corresponding to 208 ± 31 , 584 ± 51 , and 1149 ± 59 lux, respectively. When the lights were turned off, the illuminance meter gave a reading of zero lux. When all the lights were turned on at full strength, the sensor gave an average reading of 1149 lux. The color temperature of the lighting was measured to be 5600 K, corresponding to white light. Colored tape was placed on the ground to demarcate the locations where participants should stand during the experiment (i.e., 1.5, 4.5, and 7.5 m from the sensor array).

Before entering the study environment, the participants were asked to provide their gender identity and evaluate their skin tone according to the [Monk Skin Tone \(MST\) Scale](#) to evaluate algorithmic bias. The study evaluated algorithmic bias by bucketing skin tone into three categories: light (MST 0-4), medium (MST 5-7), and dark (MST 8-10). At each location and lighting condition, ten readings were taken from each sensor and averaged.

Participants were recruited using flyers, and those interested filled out a Study Interest Form. Upon arrival, participants signed a Consent Form indicating their willingness to participate in the study. The accuracy of the model is provided in the following graphs as a function of lighting condition, distance, gender identity, and skin tone. Overall, 63.2% of the participants were male, and 36.8% were female; the percentage of participants corresponding to each skin tone group was: 47.4% light, 39.4% medium, and 13.2% dark.

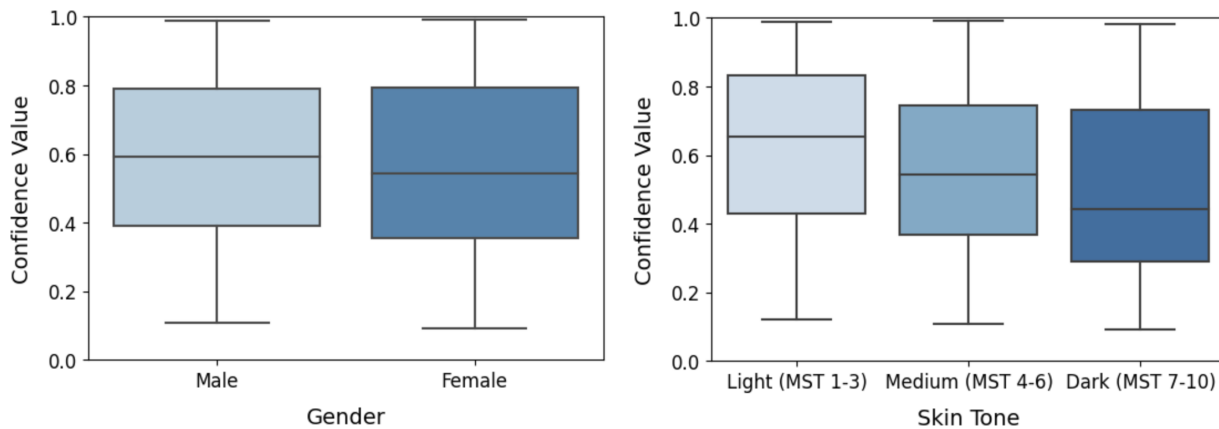
Environmental Sensitivity

The device shows a marginal decrease in performance under decreased lighting conditions. A marked drop off in performance is observed at distances 3-5 meters from the sensor.



Demographic biases

A small gender bias is observed in model performance. A large skin tone bias was observed, showing approximately a 20% decrease in the confidence value for individuals with a darker skin tone.



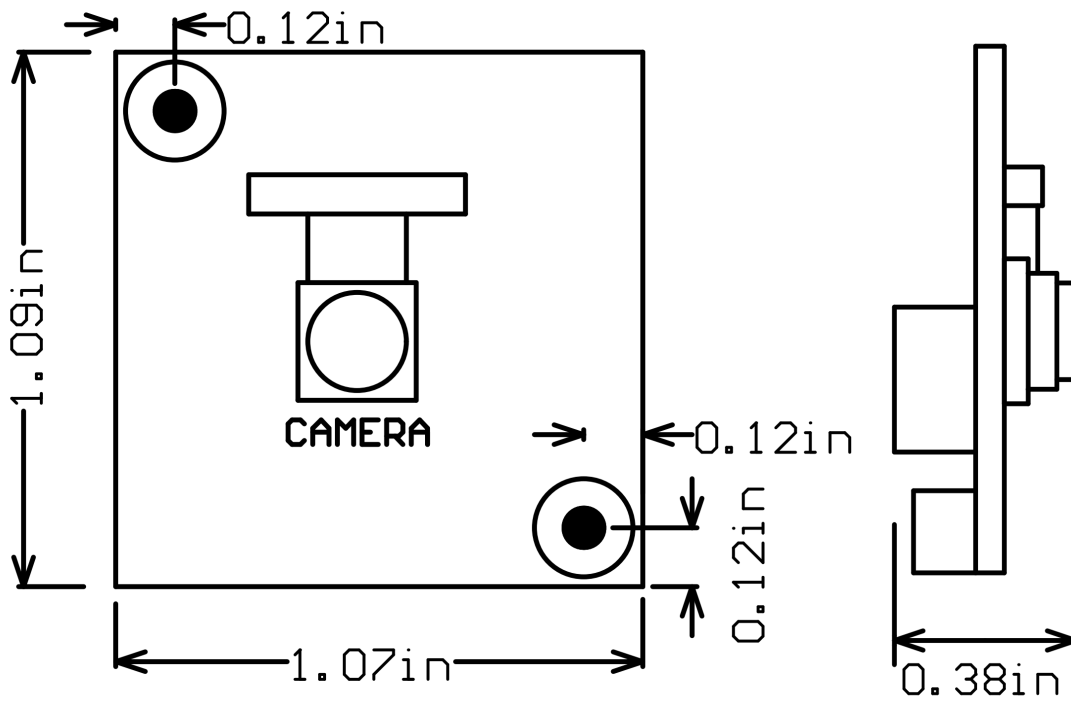
HARDWARE CHARACTERISTICS

Hardware Details

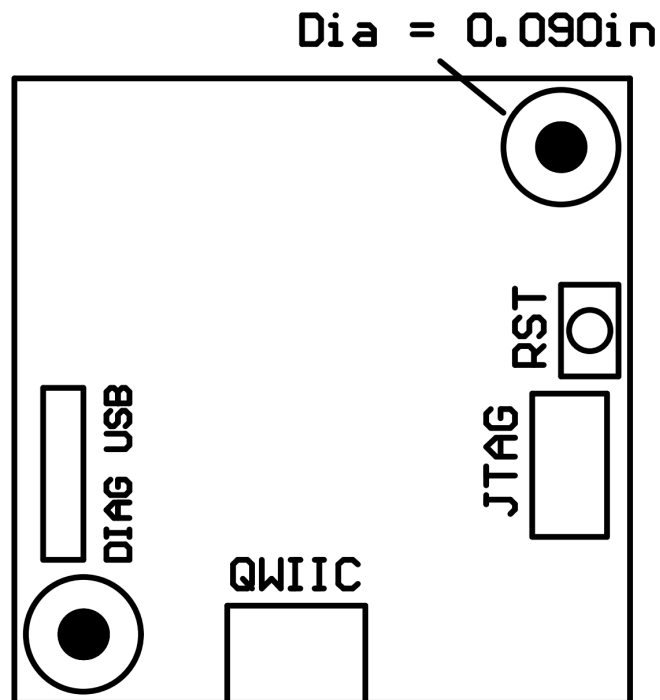
Camera Specifications (see here)	
Field of view (horizontal)	87°
Color Filter Array	Bayer, Monochrome
Frame Rate	45FPS @ 6MHz
Pixel Array (Active/ Effective)	324 x 324 / 320 x 320
Electrical Specifications	
Operating Voltage Range (regulator enabled)	3.5V to 5.5V
Operating Voltage Range (regulator disabled)	3.0V to 3.6V
Operating Current	40 mA
Operating Temperature	-20 °C to 85 °C
Communication Specifications	
I2C/Qwiic mode	Conforms with SparkFun Qwiic electrical/mechanical specifications. https://www.sparkfun.com/qwiic
Max cable length	1 m
Max data rate	100 kb/s
Module Orientation	Red arrow on sticker points up.
GPIO mode	SCL/SDA lines can be customized to make programmable flag lines ($I_{out\ max} = 12\ mA$)
Diagnostic LED	Default behavior of green LED on board: illuminates for one second on power-up, then illuminates when person detected.
Data Transfer and Format	Single byte: number from 0-255 representing confidence score
I2C Address	TBD

Device Diagrams

Front and side view of sensor.



Back view of sensor.



Bill of Materials

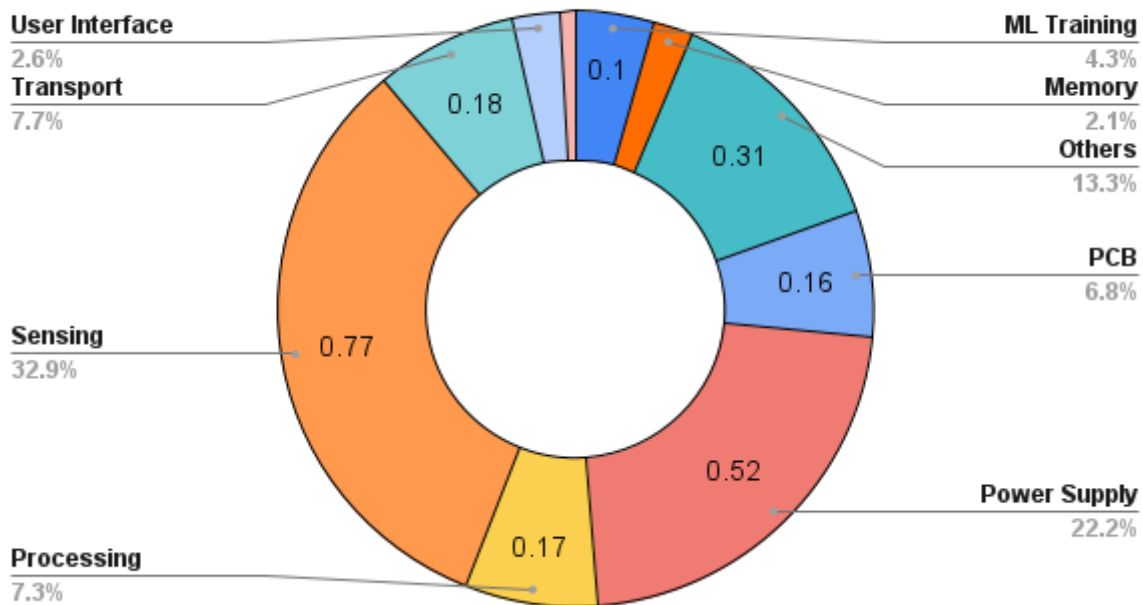
The following is a comprehensive list of materials required to assemble the PA1 person detection module, commonly referred to as the bill of materials. All unit cost values quoted in minimum order quantity of one.

Category In TinyML Calculator	Component	Unit Cost (\$)	Quantity	Manufacturer	Link to Datasheet (if available)
Functional Components					
✓	RP2040 Microcontroller	1.00	1	Raspberry Pi	https://datasheets.raspberrypi.com/rp2040/rp2040-datasheet.pdf
✓	QVGA Camera Module HM01B0	8.90	1	HiMax	https://cdn.sparkfun.com/assets/7/f/c/8/3/HM01B0-MNA-Datasheet.pdf
✓	Flash Memory W25Q16JVSNIQ	0.36	1	Winbond Electronics	https://www.winbond.com/resource-files/w25q16jv%20spi%20revg%2003222018%20plus.pdf
✓	12 MHz Crystal Oscillator 445C25D12M00000	0.42	1	CTS-Frequency Controls	https://www.mouser.com/datasheet/2/96/008-0360-0-786290.pdf
Power Circuitry					
	Voltage Regulator TLV70228 2.8V	0.69	1	Texas Instruments	https://www.digchip.com/datasheets/download_datasheet.php?id=3747267&part-number=TLV70228
Indication					
✓	LTST-C190KGKT LED	0.05	1	Lite-On Inc.	https://www.digikey.com/htmldatasheets/production/37809/0/0/1/ltst-c190kgkt.pdf
Connectors					
	FFC connector FH26W-31S-0	1.28	1	Hirose Electric Co Ltd	https://www.hirose.com/product/download/?distributor=digikey&type=specsheet&lang=en&num=FH26W-31S-0.3SHW(60)
	Qwiic connector PRT-14417	0.57	1	SparkFun Electronics	https://www.mouser.com/datasheet/2/813/Owiic_Connector_Datasheet-1223982.pdf
Passive Components					
✓	Resistors	0.01	10	-	N/A
✓	Capacitors (low value)	0.01	15	-	N/A
✓	Capacitors (high value)	0.05	7	-	N/A
✓	Ferrite bead 600Ω	0.07	2	-	N/A
✓	Printed circuit board	0.50	1	-	N/A
	Total	14.51			

Environmental Impact

With the widespread deployment of smart sensors, it is essential to consider and be conscious of the environmental impact such ubiquitous computing may have. Thus another component we advocate to be included in the datasheet is an “environmental impact” section that outlines the device footprint. Using the methodology of [9], we generated a sample of what this section might look like as part of the datasheet for our sensor specifically. We capture the carbon footprint (CO₂-eq.) of our ML sensor in the chart below. Due to the limited amount of data available on electronic device footprint we were not able to capture every single component. We were able to account for 10 out of 13 components from our bill of materials, though, which we feel captures the concept sufficiently for the sake of demonstration. We were unable to find data for the connectors and voltage regulator. However, in addition to the bill of materials, we capture the carbon footprint for the ML sensor’s model training, transport, and three-year use.

The total carbon footprint, including embodied and operational footprint, of our ML Sensor is approximately **2.34 kg CO₂-eq.** The chart below shows how the footprint is broken down. The majority of the footprint can be attributed to the power supply and camera sensor.



We note that we do not claim that this is 100% accurate but rather a representative approximation of the sensor’s environmental impact and what other future datasheet should aim to include.

Acronyms

Acronym	Description
SNR	Signal-to-noise ratio
COCO	Common Objects in Context
FFC	Flexible Flat Cable
GDPR	General Data Protection Regulation
ML	Machine Learning
I2C	Inter-Integrated Circuit
LED	Light-Emitting Diode
MCU	Microcontroller Unit
SCL	Serial Clock
SDA	Serial Data
GPIO	General Purpose Input Output
SDK	Software Development Kit
QVGA	Quarter Video Graphics Array

Glossary

Lux	Photometric unit of luminance (at 550 nm, 1 lux = 1 lumen/m ² = 1/683 W/m ²)
Sensitivity	A measure of pixel performance that characterizes the rise of the photodiode or sense node signal in Volts upon illumination with light. Units are typically V/(W/m ²)/sec and are dependent on the incident light wavelength. Sensitivity measurements are often taken with 550 nm incident light. At this wavelength, 683 lux is equal to 1 W/m ² ; the units of sensitivity are quoted in V/lux/sec. Note that responsivity and sensitivity are used interchangeably in image sensor characterization literature so it is best to check the units.
SNR	Signal-to-noise ratio. This number characterizes the ratio of the fundamental signal to the noise spectrum up to half the Nyquist frequency.
Inference	The process of applying a trained machine learning model to unseen data for making predictions or classifications. In the context of person detection, it involves analyzing images or video frames to determine if a person is present.
False Positive	A situation in person detection where the system incorrectly identifies an object or pattern as a person when it is not.
False Negative	A situation in person detection where the system fails to identify a person when one is present.
Accuracy	A performance metric that measures the overall correctness of a person detection system, indicating the percentage of correctly identified persons in the total number of instances.
Precision	A performance metric that measures the proportion of correctly identified persons among all the instances identified as persons by the system. It quantifies the system's ability to avoid false positives.
Recall (Sensitivity)	A performance metric that measures the proportion of correctly identified persons among all the actual persons present in the data. It quantifies the system's ability to avoid false negatives.
Threshold	A predefined value used to determine whether the output of a person detection system indicates the presence or absence of a person. Adjusting the threshold affects the balance between false positives and false negatives.
Training Data	Labeled examples or samples used to teach a machine learning model to recognize and classify objects accurately. In the case of person detection, it comprises images or videos with annotated information about the presence or absence of people.
Person Detection	The process of identifying the presence and location of a person within an image or video stream.
Sensor	A device that detects and measures physical or environmental properties, such as the presence of a person, and converts them into electrical signals.