

Datasheets for Machine Learning Sensors: Towards Transparency, Auditability, and Responsibility for Intelligent Sensing

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Machine learning (ML) sensors are enabling intelligence at the edge by empowering end-users with greater control over their data. ML sensors offer a new paradigm for sensing that moves the processing and analysis to the device itself rather than relying on the cloud, bringing benefits like lower latency and greater data privacy. The rise of these intelligent edge devices, while revolutionizing areas like the internet of things (IoT) and healthcare, also throws open critical questions about privacy, security, and the opacity of AI decision-making. As ML sensors become more pervasive, it requires judicious governance regarding transparency, accountability, and fairness. To this end, we introduce a standard datasheet template for these ML sensors and discuss and evaluate the design and motivation for each section of the datasheet in detail including: standard dasheet components like the system's hardware specifications, IoT and AI components like the ML model and dataset attributes, as well as novel components like end-to-end performance metrics, and expanded environmental impact metrics. To provide a case study of the application of our datasheet template, we also designed and developed two examples for ML sensors performing computer vision-based person detection: one an open-source ML sensor designed and developed in-house, and a second commercial ML sensor developed by our industry collaborators. 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 use of sensor data.

CCS Concepts: • **Hardware** → **Sensors and actuators**; • **Computer systems organization** → **Embedded and cyber-physical systems**; • **Security and privacy** → **Privacy protections**; • **Human and societal aspects of computing** → **Ubiquitous and mobile computing systems and tools**; • **Applied computing** → **Document management and text processing**.

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1 INTRODUCTION

Intelligent capabilities enabled by artificial intelligence algorithms are rapidly maturing. We are witnessing a migration of sophisticated sensing, processing, and decision-making from the cloud down to endpoint devices themselves [44, 53]. Rather than simply collecting data to transmit elsewhere, today's smart sensors and internet-connected endpoint devices are increasingly becoming infused with their own advanced AI that equips them to interpret rich sensory data streams in real time [10, 43]. This edge-based approach is enabling innovations ranging from smart homes to wearable health trackers [36]. However, performing analytics at the source also escalates privacy and security threats. Thus, as advanced sensor systems grow more complex and powerful, the necessity for clear transparency and thorough auditability becomes increasingly vital.

Transparency and auditability in sensor systems has historically been addressed through the use of datasheets, which have played a crucial role in providing a clear understanding of electronic devices and their functionalities. These documents, essential for engineers and developers, offer a comprehensive overview of a device's characteristics and performance, including detailed specifications on power requirements, operational limits, component specifications, and performance benchmarks. This level of detail enables various stakeholders, such as developers, researchers, and consumers, to assess the suitability of a device for their needs, ensuring compatibility and efficiency in system design.

However, the landscape of sensor systems is evolving. The modern architecture of intelligent sensor systems, characterized by a complex mix of hardware and software from different vendors, along with computations performed both locally and in the cloud, presents significant challenges to the traditional approach of using datasheets for transparency and auditability [50]. The intricate interplay of components, each with its proprietary systems and standards, complicates the task of tracing functionality and diagnosing issues. Furthermore, these devices are not static; they are dynamic in nature, often receiving updates and modifications post-deployment via cloud services. This fluidity, while beneficial for keeping devices current and functional, introduces additional layers of complexity. It makes it increasingly difficult to maintain a consistent and clear understanding of a device's capabilities and behavior over time, challenging the traditional methods of ensuring transparency and auditability in sensor systems.

Several high-profile incidents have demonstrated these risks, such as baby monitors being hacked to spy on children [20] and smart home systems being compromised to enable data theft [51]. Such alarming failures have led consumers, regulators, and privacy advocates to demand greater transparency and auditability to ensure these rapidly proliferating systems operate responsibly and as intended without violating ethical or legal standards [38, 48]. There is growing pressure for tech companies to embed privacy protections and security safeguards directly into their products, rather than leave it solely to consumers to implement insecure workarounds [8, 28, 40].

In response to these challenges, developers, researchers, and policymakers are exploring new approaches and technologies to enhance the transparency and auditability of intelligent sensor systems. From designing more interpretable AI models to implementing strict security protocols, efforts are underway to ensure that the pervasive adoption of these technologies brings benefits without compromising privacy, security, or trust. One particularly appealing paradigm

toward such efforts is the machine learning (ML) sensor [50]. ML sensors represent a paradigm shift towards more integrated and self-contained devices. By leveraging tiny machine learning (TinyML) for ultra-low power applications at the edge [49], ML sensors offer a design where AI capabilities are not merely added on through cloud or mobile connectivity but are fully integrated within the sensor itself. This integration promises a more streamlined and understandable system, potentially simplifying the audit process and enhancing transparency. By consolidating the AI functionality into a single, cohesive unit, it becomes easier to understand and document how the device processes data and makes decisions, which is crucial for both transparency and auditability.

The potential of applying a datasheet framework to these advanced devices represents a promising avenue for increasing transparency and facilitating a more thorough understanding of these complex systems. With a common set of standards for what these datasheets should include, the industry could move towards more transparent, trustworthy, and user-friendly technology deployment. This could facilitate easier comparison between devices, promote best practices in design and deployment, and potentially even inform regulatory guidelines for emerging technologies.

To address these challenges and promote responsible innovation, this paper proposes a new, comprehensive datasheet structure tailored for edge devices with self-contained architectures, like the ML sensor. This datasheet not only encompasses traditional sensor characteristics but also extends to include detailed information about the on-device model, privacy, security, environmental impact, and an end-to-end performance analysis. The aim is to establish a standard that ensures the responsible and effective use of sensor data across the broader ML and embedded system communities. In summary, this paper's contributions are to promote **responsible innovation in ML sensors by:**

- Proposing and designing a comprehensive datasheet template for ML sensors, addressing the current transparency challenge and bridging the knowledge gap between ML algorithms and embedded systems.
- Pioneering the development of the first open-source ML sensor, setting a benchmark for the industry and promoting accessibility and innovation in the TinyML community.
- Demonstrating the application of the datasheet by developing a reference example for our open-source ML sensor (included as Appendix A), and a datasheet tailored for a proprietary sensor that respects and incorporates intellectual property considerations through collaboration with a commercial partner (included as Appendix B).
- Evaluating the end-to-end performance of both open-source and commercial ML sensors in an IRB-approved experimental study, providing insights into their practical application and analysis.

2 BACKGROUND AND RELATED WORK

2.1 Datasheets (for ML)

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. Developers need this information 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 [7, 45, 54]. While these studies targeted specific datasets, datasheets for datasets was proposed as a more general framework for documenting dataset characteristics [18]. The data nutrition label offers a similar diagnostic framework presenting a standardized view of a dataset's important attributes [11, 23]. IBM has also introduced the idea of factsheets to document various features of ML services in order to bolster trust [6].

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

Datasheets ↓	Hardware	Privacy & Security	Dataset	Model	Env. Impact	End-to-End
ML Sensors (our work)	✓	✓	✓	✓	✓	✓
Traditional Sensor Datasheet	✓	✗	✗	✗	✗	✗
IoT Security/Privacy Label [15, 16]	✗	✓	✗	✗	✗	✗
Data Nutrition Label [11, 23]	✗	✗	✓	✗	✗	✗
Datasheets for Datasets [18]	✗	✗	✓	✗	✗	✗
Model Cards [32]	✗	✗	✗	✓	✗	✗

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 [32]. Efforts have also been made to include relevant privacy and security information to IoT devices [15, 16]. 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 and carbon emissions [21, 39]. The growing trends in ML documentation and the increasing use of ML have highlighted the need for ethical considerations [9]. 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 [35].

Table 1 highlights the novelty of 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, while our work builds (in part) on prior developments, we assert the need to augment a traditional sensor datasheet with vital ML, IoT, and new elements into a comprehensive and extendable datasheet.

2.2 From Smart IoT to ML Sensors

An ML sensor is a self-contained system utilizing on-device ML to interpret a complex set of sensor data and relay high-level information through a straightforward interface to a wider system [50]. The features of an ML sensor deviate from those of traditional smart IoT devices. 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, bringing about enhanced privacy and security as raw data is never transmitted. Only summarized traits of the data 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.

Figure 1b shows examples of existing ML sensors used for person detection [42]. These sensors can determine if a person is present within view of the on-device camera. Importantly, the unified nature of both data collection and analysis, and the fact that ML model performance and the operating characteristics of the sensor are integrated into a single system and cannot be disambiguated from each other, both requires and enables the construction of a unified datasheet for the device, covering standard datasheet components as well as IoT, AI, and other emerging components.

3 THE ML SENSOR DATASHEET

ML-enabled devices, like ML sensors, often provide hardware specifications and instructions for utilizing the sensor's capabilities, but may lack substantial details regarding the training data used for the on-device models, including information on data characteristics, distributions, and potential biases which would build trust in model performance; model architecture and benchmarks, with details on design choices and performance evaluations on standard datasets

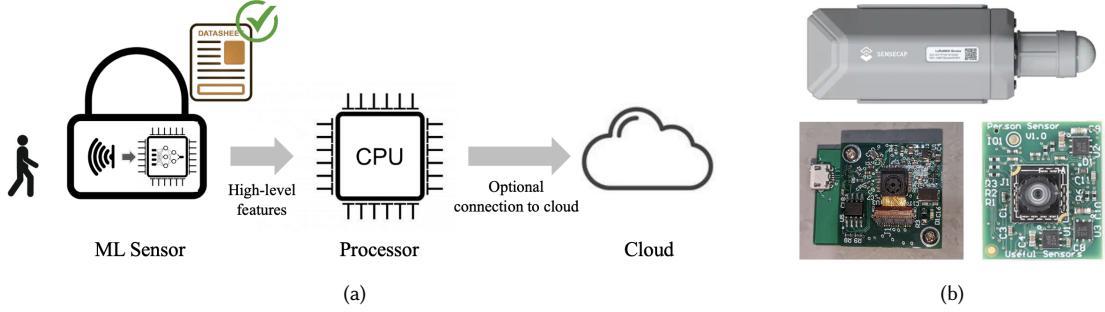


Fig. 1. (a) The ML sensor paradigm. (b) Examples of existing ML sensors; (top) Seeed Studio’s SenseCAP LoRaWAN sensor [41], (bottom left) our own person detection sensor whose design is publicly accessible (see <https://anonymous.4open.science/r/ML-Sensors-B543>), and (bottom right), Useful Sensor’s person sensor [42]. We will be using our person detection sensor as the prime example for how we developed the ML sensor datasheet.

allowing better assessment of expected capabilities; environmental impact over the device lifetime, including materials, energy use, and recyclability allowing more sustainable adoption; robustness to anticipated changes in operating conditions once deployed, with testing results on transformations in factors like lighting, backgrounds, weather, and wear guiding appropriate scenarios; aspects of privacy, security, and compliance such as disclosure and protections around data sharing, vulnerabilities, and regulatory conformance improving transparency and lowering risks.

Providing comprehensive documentation in these areas can increase user trust, facilitate accountability, and encourage responsible development and adoption of ML innovations across industries. The information also enables those deploying ML systems to better ensure outcomes align with their principles. To address these needs, we present what we believe should be the sections of a unified ML sensor datasheet. Our datasheet format, as shown in Figure 2, is segmented into several key areas:

- **Standard Sensor Datasheet Components.** This section follows the conventional format, encapsulating fundamental sensor information such as a detailed description, features, use cases, communication specifications, pinout details, compliance with industry standards, as well as physical attributes like diagrams and form factors, and the hardware characteristics that describe the sensor’s technical specifications.
- **IoT Datasheet Components.** Dedicated to the integration of the sensor within Internet of Things ecosystems, this part outlines privacy and security protocols specific to IoT, ensuring that the sensor’s deployment aligns with modern cybersecurity practices.
- **AI Datasheet Components.** This innovative segment provides in-depth information about the AI models embedded in the sensor, including the type of algorithms used, the training data, and any pertinent model characteristics that users and developers should be aware of.
- **Additional ML Sensor Datasheet Components.** To address the specific needs of ML sensors, this section adds layers of analysis including the environmental impact, showcasing the device’s footprint and sustainability, and an end-to-end performance analysis which reviews the sensor’s functionality in real-world scenarios, considering factors like varying environmental conditions and fairness parameters.

This datasheet format incorporates best practices from existing literature and insights from our development of an open-source, commercially-relevant machine learning (ML) sensor. In Sections 3.1–3.4, we provide a detailed breakdown of the four key components of the datasheet in the remainder of this section.

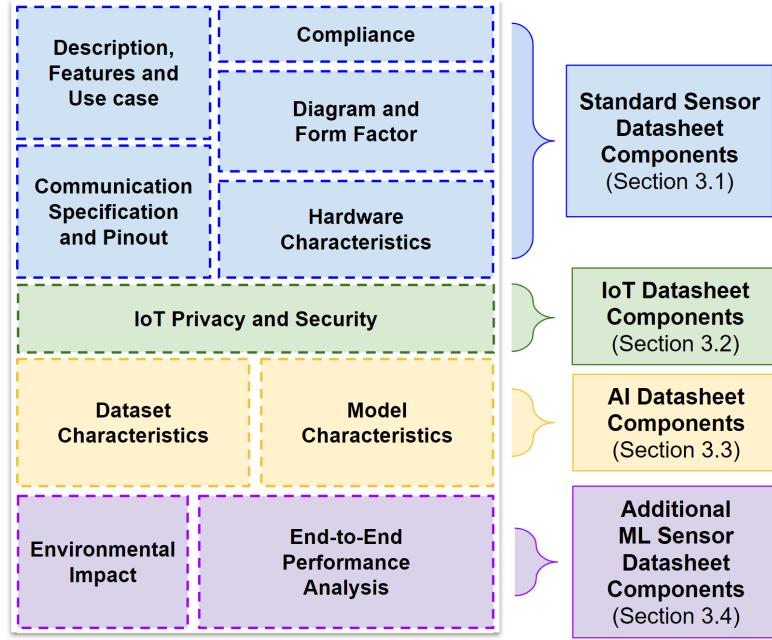


Fig. 2. Schematic of the proposed datasheet template for ML sensors. The core of the template encompasses standard sensor datasheet components which include hardware characteristics, communication specification, and device diagrams, outlined in blue. The IoT Datasheet Components section, highlighted in green, addresses IoT privacy and security, ensuring the sensor's adherence to data protection and network security standards. The AI Datasheet Components section, colored in yellow, delves into the specifics of the sensor's AI capabilities, with a data nutrition label for data transparency and model characteristics for a deeper understanding of the embedded AI model. Additional components relevant to the ML sensor are depicted in purple, which introduce novel elements such as environmental impact, which considers the ecological footprint, and end-to-end performance analysis, which evaluates the sensor's performance across various deployment scenarios. Each section is referenced to further detailed subsections, indicating the extendable nature of the datasheet in covering every facet of the sensor's design, functionality, and societal impact.

3.1 Standard Datasheet Components

The standard datasheet components section of the ML sensor datasheet provides general technical specifications and information to help developers and users understand the device's basic capabilities and its suitability for their task.

3.1.1 Description, Features, and Use Case. *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.

3.1.2 Diagrams and Communication Specification. *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.

3.1.3 Hardware Characteristics. 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.

3.1.4 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 [37], radio frequency usage guidelines like FCC regulations, or industry-specific requirements like HIPAA [3] or FDA standards in healthcare. This section could also showcase adherence to voluntary industry-specific best practices, such as ISO 26262 standard [26] for autonomous vehicles or IEC 61508 [25] 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.

3.2 IoT Datasheet Components

Transparency regarding security and privacy is crucial for building trust in IoT devices. This section summarizes the ML sensor's safeguards and risks, facilitating awareness and informed decision-making when purchasing smart devices.

3.2.1 Security and Privacy. *What security and privacy features does the ML sensor have?* This label promotes 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 [16]. The label covers privacy-related aspects such as data collection, retention and transmission practices, security mechanisms (e.g., encryption, automatic security updates), as well as the types of sensors present on the device and their associated data modalities. The primary layer is intended for display on product packaging or online shopping platforms, while the secondary layer is accessible through the QR code on the primary layer, offering further valuable insights for those seeking a deeper understanding of a device's potential risks and safeguards.

While not mandatory, information regarding the updateability of the device’s ML models could also be included in this section, although doing so increases the attack surface of the device, leaving it vulnerable to a wider range of security and privacy risks. Model updateability refers to the ability of the device to receive and implement over-the-air updates to its ML algorithms, ensuring that it remains secure against emerging threats and continues to perform optimally. This could be achieved through regular firmware updates provided by the manufacturer, which the device can download and install automatically or after user approval. Including details about the frequency, method, and security measures of these updates can further inform users about the longevity and reliability of the device’s performance.

3.3 AI Datasheet Components

Transparency regarding dataset provenance, content, and quality builds accountability in AI systems. This section details the data used for training, enabling stakeholders to evaluate aspects like sampling, measurement, and bias.

3.3.1 Dataset Characteristics. *What data is the model trained on?* Outlining dataset characteristics is fundamental for ensuring transparency in ML systems. This transparency is crucial because it allows users, developers, and regulators to understand how and why a ML model makes certain decisions, and to assess its fairness, accuracy, and potential biases. By clearly detailing the nature of the training data, stakeholders can better evaluate the model’s applicability to real-world scenarios and its alignment with ethical standards. Several approaches have been proposed to achieve this, including datasheets for datasets [18] and the data nutrition label [23].

Taking the data nutrition label as an example, 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 [27, 31].

3.3.2 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.

3.4 ML Sensor Datasheet Components

As IoT proliferation increases e-waste, consumers must be informed of devices’ environmental sustainability. Similarly, as these devices are deployed in increasingly diverse environments, users must be able to understand how their performance will vary. This section outlines the end-to-end performance variability and environmental consequences of deploying these devices across real-world settings enabling the full embodied device to evaluated by users.

3.4.1 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 [46]. However, embedding smart computing into everyday objects has looming environmental consequences through increased electronic waste [22]. With this widespread deployment, the environmental impact of these devices must be considered. Therefore, another component we advocate to be included in the datasheet is an “environmental impact” section that outlines the device’s footprint.

3.4.2 End-to-End 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.

4 A CASE STUDY IN PERSON DETECTION

In this section, we present a detailed case study of two person detection ML sensors (shown previously in Figure 1b). The first is an open-source ML sensor, developed as part of this research initiative. This sensor represents our foray into creating accessible, transparent tools in the realm of machine learning, with a focus on fostering reproducibility and collaborative development in the research community. The complete specifications and operational details of this sensor are thoroughly documented in Appendix A. Complementing our open-source sensor, we also collaboratively examined a commercially-oriented ML sensor developed by a commercial partner. This partnership allowed us to integrate academic research insights with practical, industry-standard design approaches. The result is a sensor that not only meets commercial viability criteria but also achieves increased auditability and transparency. The full datasheet of this commercial sensor, including its design and performance characteristics, is available in Appendix B.

The juxtaposition of these two sensors in our case study serves multiple purposes. Firstly, it provides a comprehensive overview of the current state of person detection technology, spanning both open-source and commercial domains. Secondly, it offers insights into the different design and development methodologies employed in academic versus commercial settings. Lastly, this case study aims to highlight the potential synergies between academic research and industry practices, suggesting a model for future collaborative efforts in the field of ML and sensor technology.

4.1 Standard Datasheet Components

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.” Examples of diagrams and hardware specifications for our open-source person detector are shown in Figure 3, again with the full datasheets provided in Appendix A and B. Figure 3 (*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 [2], allowing a data transfer rate of up to 100 kB/s. Figure 3 (*middle*) and (*right*) show the data standard and open-source

schema we developed for communication [1]. 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.

Additionally, while our own ML sensor has not obtained specific certifications or verification of compliance to standards, this would be appropriate for commercial devices. Currently, no certification body or standards exist specifically for ML sensors, but a mechanism could be implemented that is tied to existing non-profit entities (e.g., the [TinyML Foundation](#) or the [International Telecommunication Union](#)).

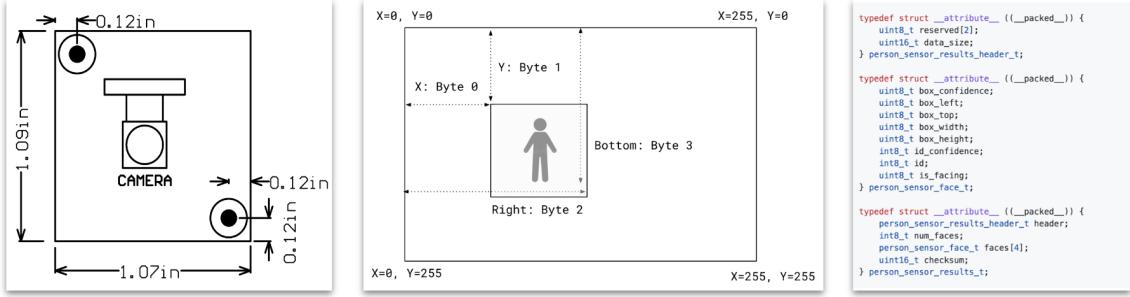


Fig. 3. (left) Device diagram of person detection ML sensor, (middle) standard for data communication, and (right) schema for communication of data off-sensor.

4.2 IoT Datasheet Components

For our ML sensor, the IoT security and privacy label (see Figure 4 left) shows that there is only a camera on the device collecting data continuously, but this data is not being stored or transmitted off-device. The self-contained nature of the ML sensors means that they have limited networking capabilities, and thus privacy concerns from the transmission of raw data are minimal. No security mechanisms are implemented due to the severe resource constraints of the device.

Security Mechanisms	Security updates ① No security updates	Access control ① Not disclosed		
Data Practices	Sensor data collection ② Visual	Audio	Physiological	Location
	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 Other collected data Not sold			
Privacy policy ① Not disclosed				

About humans
Yes

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

Upstream sources
Yes

COCO Dataset

Technical review
Yes

Update frequency
No

Not Applicable

Fig. 4. Primary IoT security and privacy label for the open-source person detection ML sensor (left), as well as its data nutrition label summary statistics (right).

4.3 AI Datasheet Components

To evaluate the dataset used in training the on-device model, we utilize the second-generation Dataset Nutrition Label [11, 23]. Summary statistics for the data nutrition label for the open-source person detection sensor are shown on the right side of Figure 4, and the full label is available in Appendix A. This label highlights that the dataset, the Visual Wake Words dataset [12], is from an upstream source (MS-COCO [29]), contains information about humans obtained without consent, and that the dataset is not currently managed or updated by any entity. Figure 5 shows some example model characteristics of the ML sensor running a MobileNetV1 architecture [24] 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.

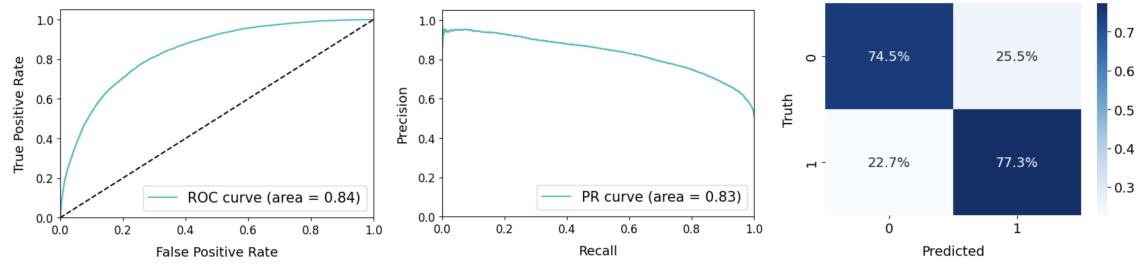


Fig. 5. ROC curve (left), precision-recall curve (center), and confusion matrix (right) for the person detection ML sensor evaluated on a test set. The confusion matrix was calculated with the optimal threshold value of 0.52.

4.4 ML Sensor Datasheet Components

4.4.1 Environmental Footprint. We captured the carbon footprint of our ML sensor using the methodology of Prakash et al. [39]. The calculator includes fields for processing, sensing, power supply, memory, and more, enabling us to input specifications from our bill of materials. Furthermore, we also capture the carbon footprint for the ML sensor’s model training, transport, and three-year use. While training costs can be amortized over multiple sensor deployments, we consider them separately to provide a conservative carbon footprint estimate. The total footprint of our ML sensor, including embodied and operational carbon, is approximately 2.34 kg CO₂-eq. Figure 6 shows that the majority of the footprint is attributable to the power supply and camera sensor. We note that other environmental impact indicators should ideally also be included in future datasheets. However, this would require 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 analysis.

4.4.2 End-to-End Performance Analysis. We present an exemplary case study of end-to-end performance analysis on our open-source person detection sensor in Figure 8, using data from three sensors to capture device variability. Such a case study was deemed necessary to assess sensor performance in a deployment environment to determine the extent of dataset shift resulting from the use of different hardware (i.e., the onboard camera), embedded demographic biases, as well as biases related to environmental changes (e.g., lighting and distance from the camera).

The end-to-end performance of the person detection sensor model was tested through an experimental study. The study involved 39 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

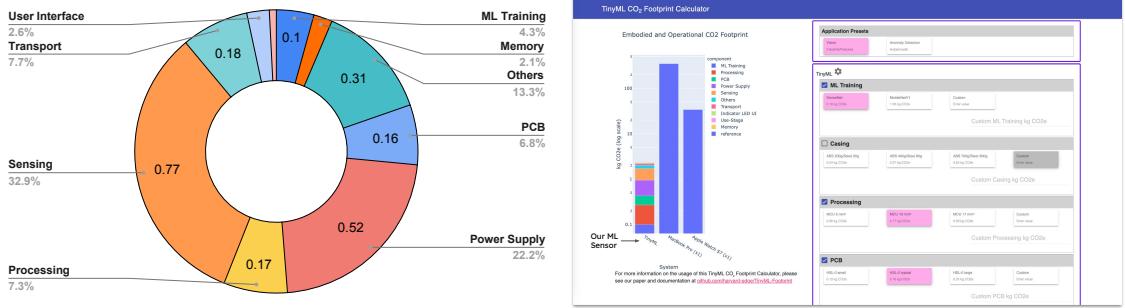


Fig. 6. Carbon footprint breakdown by component of our ML sensor (left). Units are in kg CO₂-eq. Using the TinyML Footprint Calculator from Prakash et al. [39] (right), we compute the footprint including the environmental cost for sensor transportation and ML model training. The total carbon footprint, including embodied and operational footprint, is approximately 2.34 kg CO₂-eq.



Fig. 7. This figure presents a dual-view illustration. The left panel shows a wall-mounted sensor assembly, consisting of sensors developed in-house on the left side and those provided by a commercial partner 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.

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 m, 3 m, and 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 (see Figure 7). 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, 3, and 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 (see Figure 8) is provided as a function of lighting condition, distance, gender identity, and skin tone. We note that 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.

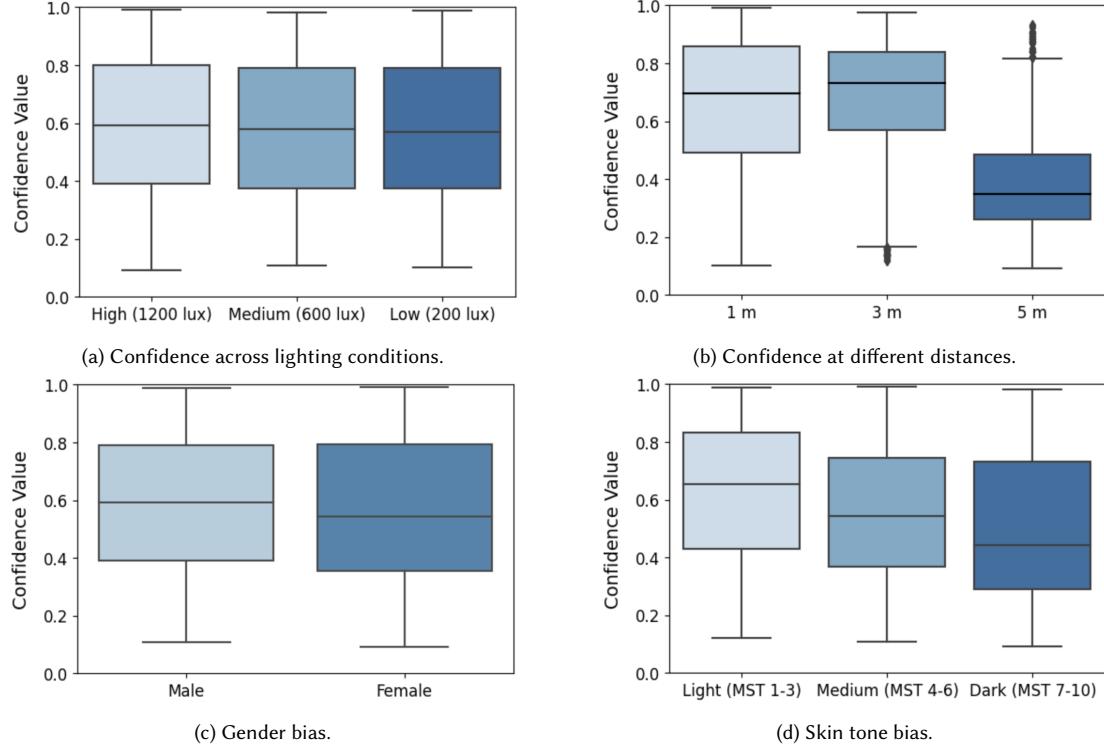


Fig. 8. End-to-end performance analysis of the ML sensor tested on 38 volunteers under controlled laboratory conditions. Skin tone was estimated using the Monk Skin Tone (MST) Scale [14].

These analysis provide examples of both device efficacy 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 8a shows that lighting conditions had little impact on performance, likely as a result of the high contrast testing environment, while Figure 8b shows that performance degraded sharply when distance increased from 3-5 meters. Figures 8c, and 8d 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.

5 DISCUSSION AND LIMITATIONS

Our datasheet template finds relevance in numerous practical applications, including predictive maintenance in industrial settings [33], environmental monitoring [19, 34], healthcare diagnostics [47], autonomous vehicles [13], and smart

homes [52]. 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. In the remainder of this section, we discuss the differences between open-source and commercial ML sensor datasheets, the generalizability of this approach to other data modalities, the limitations of our proposed approach that will require improvements as new sensors emerge, as well as additional directions for future work. Importantly, we find that our high-level template can be easily adapted for both a wide range of current and future applications but additional development is needed to specify detailed metrics and domain-specific requirements.

5.1 Open-Source vs. Commercial Comparison

At a high-level, the datasheet template was found to be applicable for both our open-source sensor, as well as the commercial sensor, with changes only necessary in a limited number of sections. Sections where changes were necessary were mainly in the data nutrition label and the model characteristics in order to obfuscate aspects of the commercial partner’s intellectual property, such as proprietary datasets, models, and training procedures. This obfuscation was critical to enable industrial collaboration and care will need to be taken in the future to ensure that the level of obfuscation balances transparency and intellectual property.

That said, we found it challenging to directly compare end-to-end results from both devices due to the differing approaches utilized by the two sensors. In particular, the commercial sensor utilized a face detection bounding-box model with a detection threshold set at ~ 0.6 , whereas our open-source sensor focused on person detection within the full image. This along with differences in camera specification meant that the open-source device was better at detecting individuals over longer distances as compared to the commercial sensor, but the commercial sensor had a wider angle of detection over the open-source sensor. This suggests that future research is needed to design and build methods to fairly compare and evaluate different output types for similar applications in order to provide relevant comparisons as the diversity of ML sensor devices grows.

5.2 Limitations

One limitation of our datasheet is the need to test the adaptability of the template to diverse sensor types, like those implementing basic neural network operations [30] or for event cameras used in VR/AR [5, 17]. While event-based cameras have different properties than CMOS cameras and utilize alternative approaches such as spiking networks over convolutional networks, datasheets for sensors using either camera type will retain similar sections such as optical properties of the camera and the network training process. We believe that incremental refinement of the datasheet template will address this challenge. A second limitation is that the datasheet relies on the accuracy and honesty of the information provided by the manufacturers or developers, with the potential risk of misinformation, misinterpretation, or lack of updates to the datasheet after product updates. That said, as mentioned in Section 3.1.4, oversight mechanisms such as certification from a trusted third-party entity could resolve this concern, and the use of blockchain technologies could aid in auditability [4].

5.3 Future Work and Directions

In looking towards the future, our datasheet template opens up numerous avenues for further exploration and specification. 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 cross-device compatibility.

6 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. Datasheets for two real-world ML sensors were designed and developed to illustrate the practical application of these datasheets, highlighting their potential to enhance transparency, auditability, and user-friendliness in ML-enabled systems for both open-source and commercial devices. 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. Example Data Sheet - Open-Source 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

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

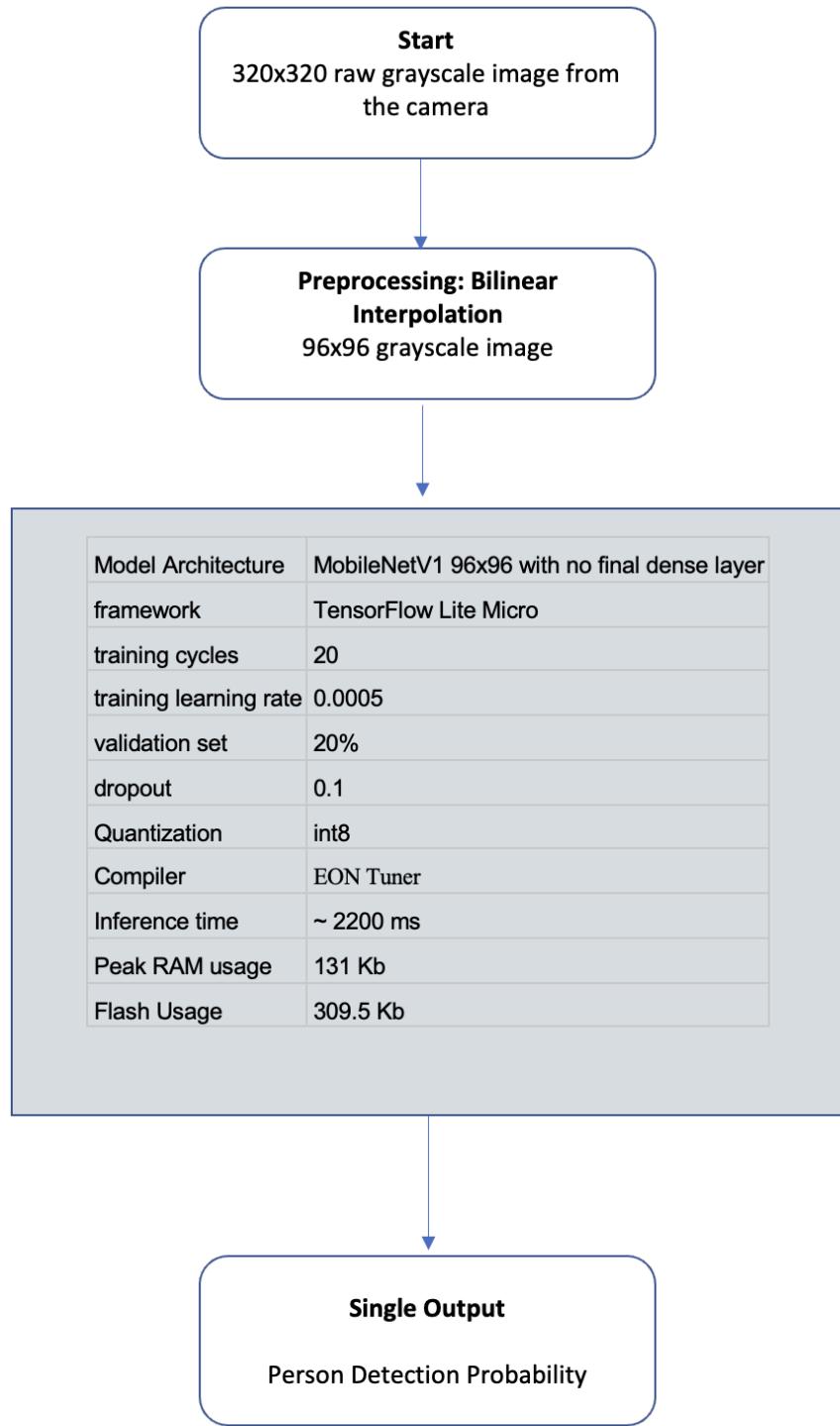
Use Cases

- 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

The data nutrition label is publicly available [here](#), with some important features outlined below.

At a Glance				
About humans	Upstream sources	Technical review	Ethical review	Update frequency
Yes	Yes	Yes	Unsure	No
COCO Dataset		https://arxiv.org/pdf/1906.05721.pdf	Not Applicable	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. Relabeling 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

Number of issues

Risky	2
Safe	1
Unknown	4

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	1
Safe	1
Unknown	2

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

Representation

Which rows were included and why?

Subpopulation Information

Not Applicable

Number of issues

	Number of issues
Risky	1
Safe	0
Unknown	5

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

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.

Number of issues

	Number of issues
Risky	1
Safe	0
Unknown	4

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

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																																									
<h1>Harvard University</h1>																																									
<p>Person Detection Module PA1 Firmware version: 0.1 - updated on: 2023-02-20 The device was manufactured in: United States</p>																																									
<table><tbody><tr><td> Security Mechanisms</td><td>Security updates (i) No security updates</td></tr><tr><td></td><td>Access control (i) No user account is allowed</td></tr></tbody></table>		 Security Mechanisms	Security updates (i) No security updates		Access control (i) No user account is allowed																																				
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	Access control (i) No user account is allowed																																								
 Data Practices	<table><tbody><tr><td>Sensor data collection</td><td> Visual</td><td> Audio</td><td> Physiological</td><td> Location</td></tr><tr><td>Sensor type</td><td>Camera</td><td></td><td></td><td></td></tr><tr><td>Purpose</td><td>Providing and improving device functions</td><td></td><td></td><td></td></tr><tr><td>Data stored on the device</td><td>No device storage</td><td></td><td></td><td></td></tr><tr><td>Data stored in the cloud</td><td>No cloud storage</td><td></td><td></td><td></td></tr><tr><td>Data shared with</td><td>Not shared</td><td></td><td></td><td></td></tr><tr><td>Data sold to</td><td>Not sold</td><td></td><td></td><td></td></tr><tr><td>Other collected data</td><td></td><td></td><td></td><td></td></tr></tbody></table>	Sensor data collection	 Visual	 Audio	 Physiological	 Location	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				
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	Privacy policy (i) Not disclosed																																								
 More Information	<p>Detailed Security & Privacy Label: Not disclosed</p> 																																								
<p>CMU IoT Security and Privacy Label CISPL 1.0 iotsecurityprivacy.org</p>																																									
																																									

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

 Security Mechanisms	Security updates	No security updates <small>(i)</small>
	Access control	No user account is allowed. <small>(i)</small>
	Security oversight	No security audits <small>(i)</small>
	Ports and protocols	Not disclosed <small>(i)</small>
	Hardware safety	Not disclosed <small>(i)</small>
	Software safety	Not disclosed <small>(i)</small>
	Personal safety	Not disclosed <small>(i)</small>
	Vulnerability disclosure and management	Not disclosed <small>(i)</small>
	Software and hardware composition list	Not disclosed <small>(i)</small>
 Data Practices	Encryption and key management	Not disclosed <small>(i)</small>
	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
	Data linkage	Data will not be linked with other data sources <small>(i)</small>
	What will be Inferred from User's Data	Presence of a human <small>(i)</small>
 More Information	Special data handling practices for children	No <small>(i)</small>
	In Compliance with	GDPR <small>(i)</small>
	Privacy policy	Not disclosed <small>(i)</small>
	Call Harvard University with your questions at	Not disclosed <small>(i)</small>
	Email Harvard University with your questions at	ml-sensors@googlegroups.com <small>(i)</small>
	Functionality when offline	Full functionality on offline mode <small>(i)</small>
	Functionality with no data processing	Not disclosed <small>(i)</small>
Physical actuators and triggers		Device performs customized actions when person is detected.
Compatible platforms		Not disclosed <small>(i)</small>

Machine Learning Model Specification

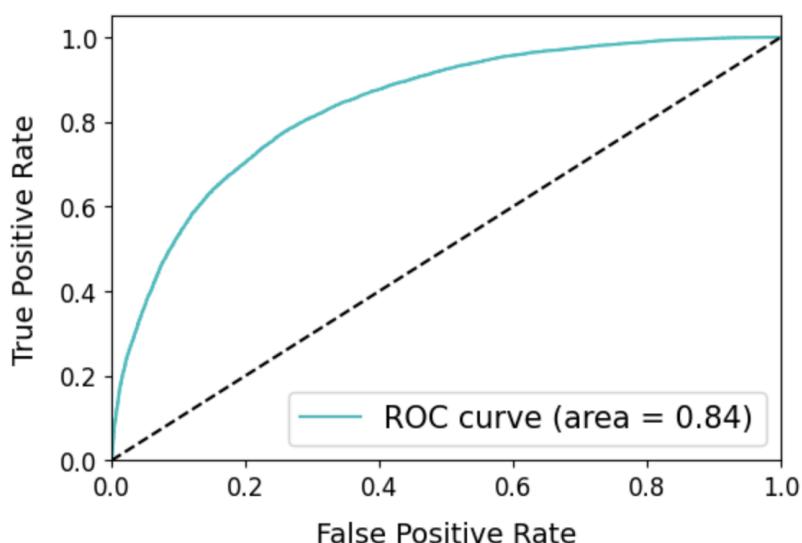
The person detection model was created using transfer learning with the [MobileNetV1](#) neural network (see architecture [here](#)) on Edge Impulse. The training and testing of the model were done using a subset of images from the [MS-COCO 2017 dataset](#), which is widely used for image recognition. 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/validation split ratio of 0.8 was used.

The input to the model is a 96x96 raw image in 8-bit grayscale format, equivalent to 9,216 features. The training process was carried out over 20 cycles with a learning rate of 0.0005 and a test 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%.

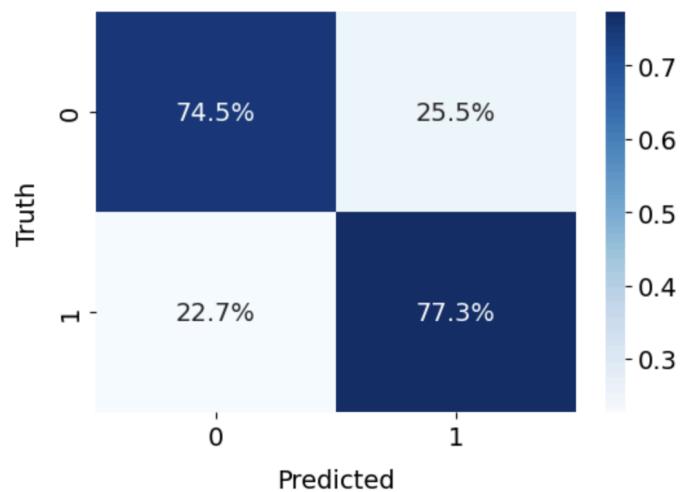
To enable live person detection, a set of image provision scripts was added to the software pipeline. The scripts continuously capture data from the onboard camera and pass it to the model in the appropriate scale and format. Using the Arm GNU Toolchain, the Pico-SDK, and the resulting C++ library, the 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](#).

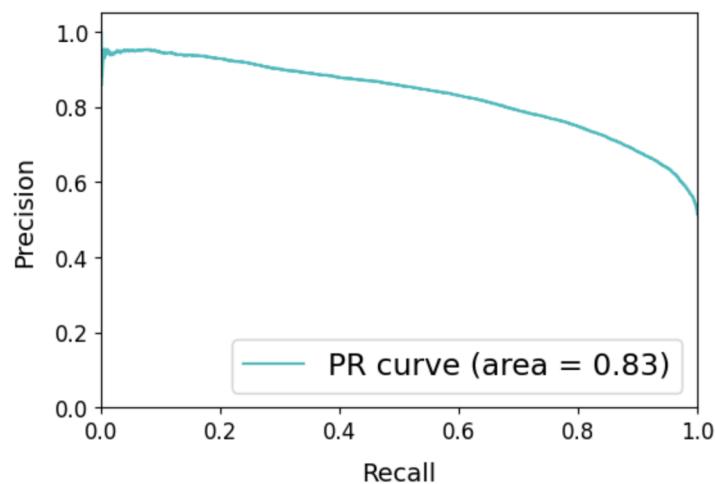
(a) Receiver Operating Characteristic Curve



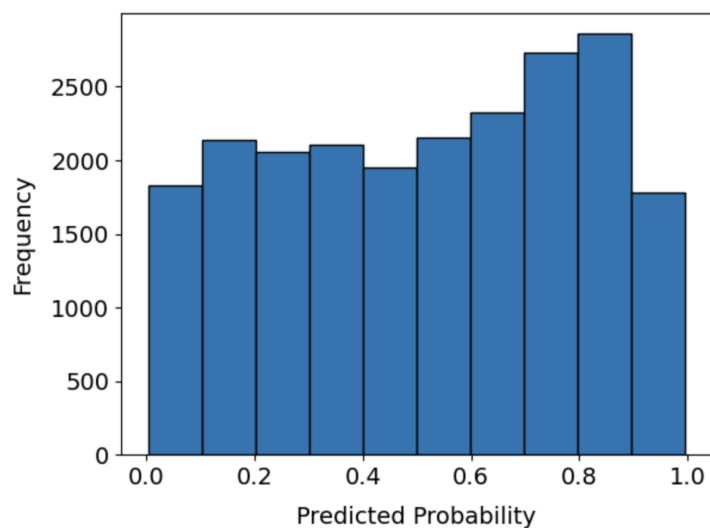
(b) Confusion Matrix



(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. 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.

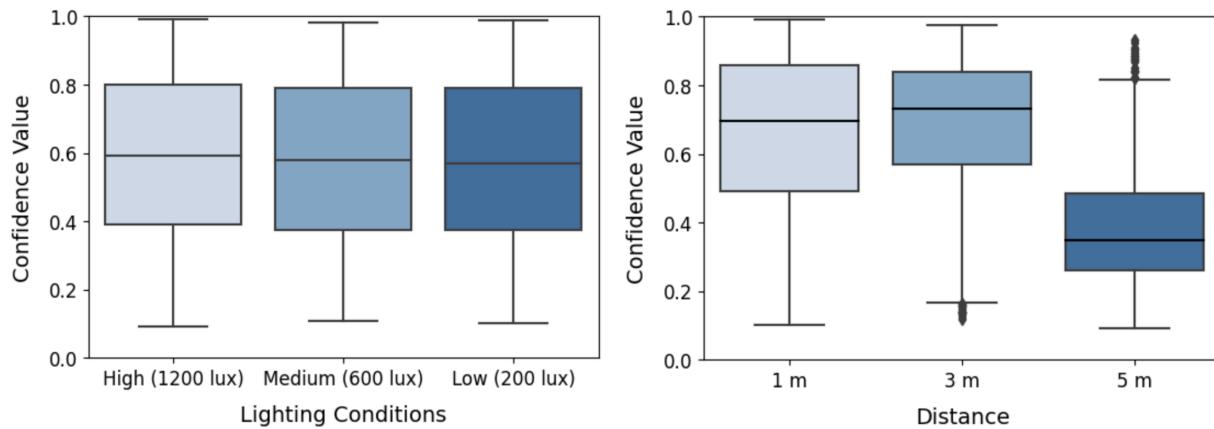
The lighting levels were controlled using a dimmer switch that had three levels of operation, corresponding to 208 ± 31 , 584 ± 51 , and 1149 ± 59 lux, respectively. When the lights were turned off, the illuminance meter gave a reading of zero lux. When all the lights were turned on at full strength, 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.

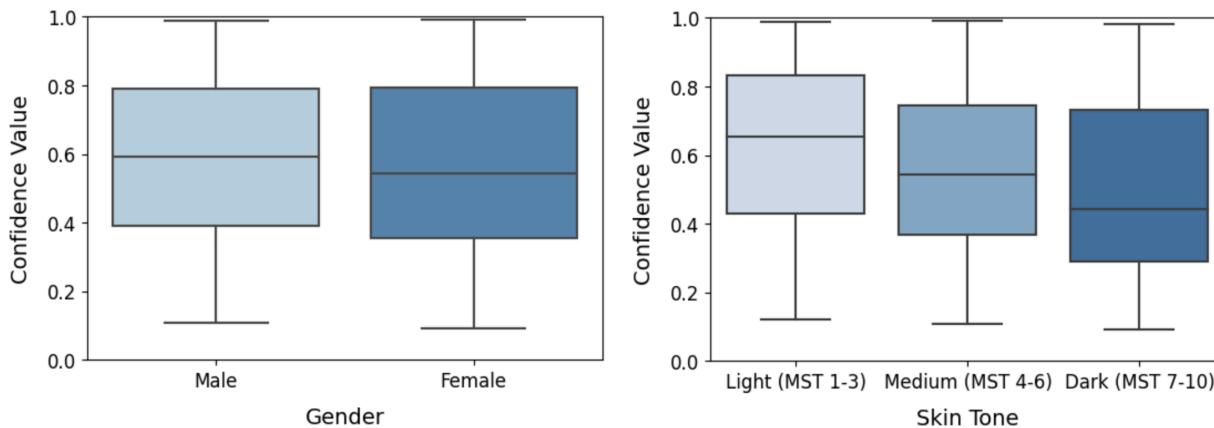
Environmental Sensitivity

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.



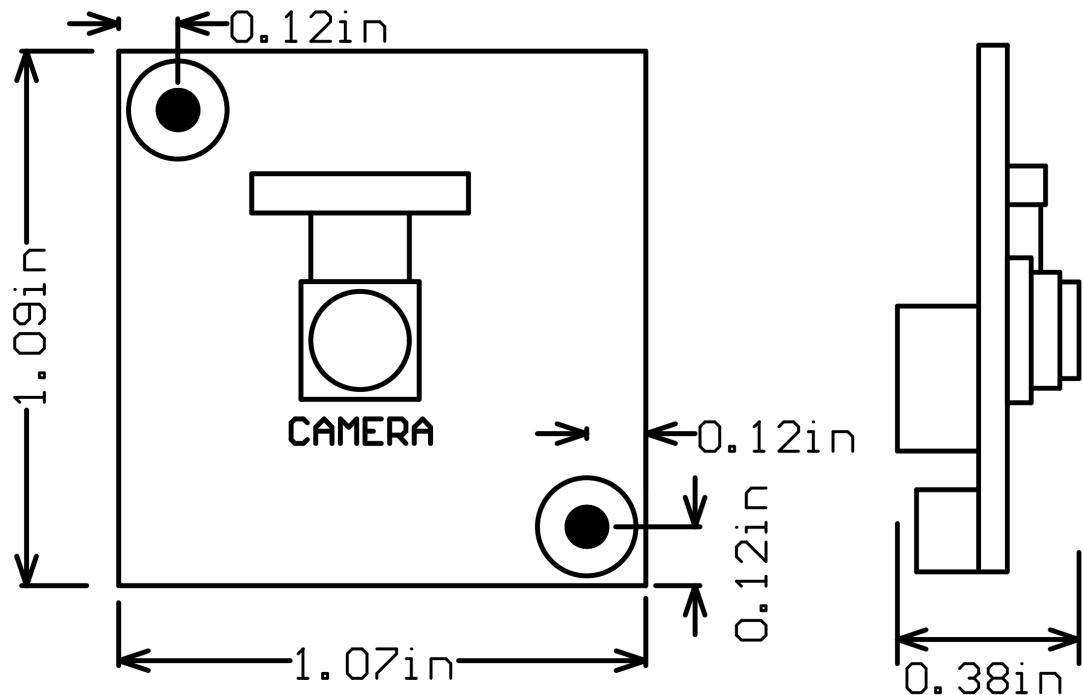
HARDWARE CHARACTERISTICS

Hardware Details

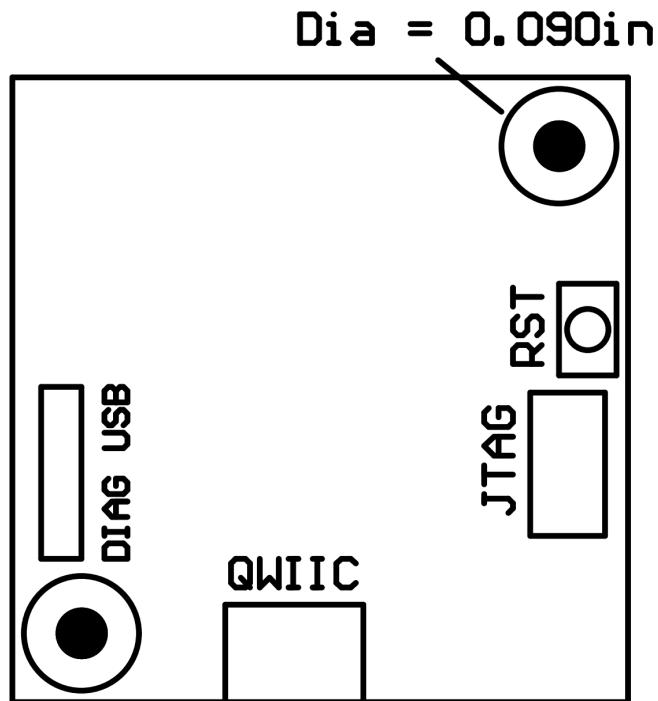
Camera Specifications (see here)	
Field of view (horizontal)	87°
Color Filter Array	Bayer, Monochrome
Frame Rate	45FPS @ 6MHz
Pixel Array (Active/ Effective)	324 x 324 / 320 x 320
Electrical Specifications	
Operating Voltage Range (regulator enabled)	3.5V to 5.5V
Operating Voltage Range (regulator disabled)	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	0x22

Device Diagrams

Front and side view of sensor.



Back view of sensor.



Bill of Materials

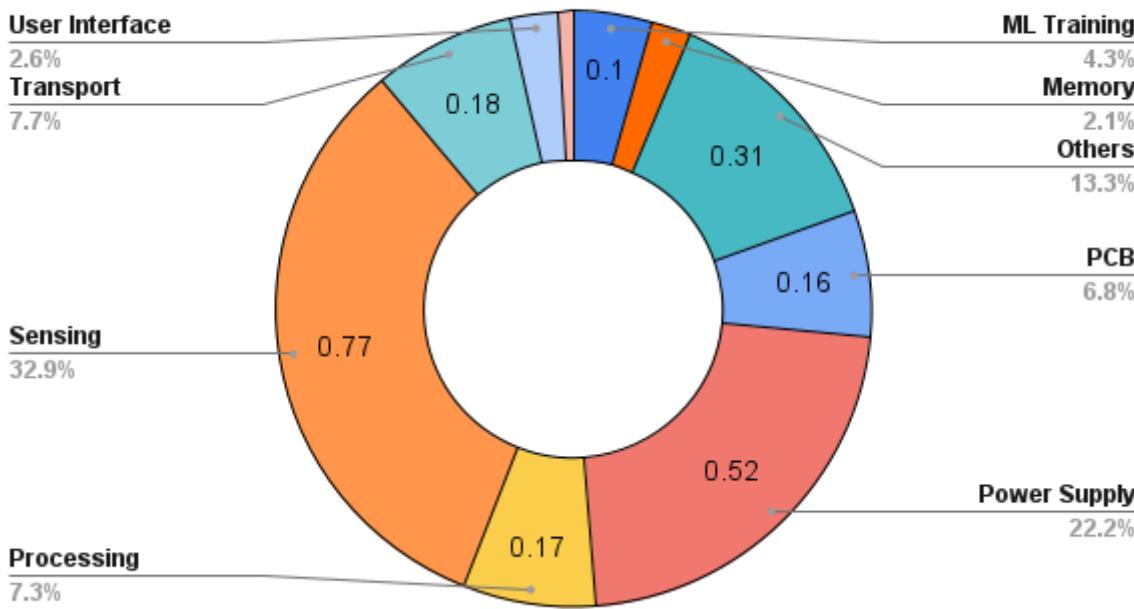
The following is a comprehensive list of materials required to assemble the PA1 person detection module, commonly referred to as the bill of materials. All unit cost values quoted in minimum order quantity of one.

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/83/HM01B0-MNA-Datasheet.pdf
✓	Flash Memory W25Q16JVSNIQ	0.36	1	Winbond Electronics	https://www.winbond.com/resource-files/w25q16jv%20spi%20revg%200322_2018%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/Qwiic_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.
Monk Skin Tone Scale	A 10-shade system, developed by Google, designed to provide a more inclusive representation of diverse skin tones in image-based technologies to address the challenges of representation in image-based technologies, especially for people of color.
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 Set	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.
Test Set	A subset of the dataset that is strictly used to evaluate the performance of a model after it has been trained. The test set provides an unbiased evaluation of a model's generalization to new, unseen data. It should never be used during training or hyperparameter tuning.
Validation Set	A subset of the dataset, separate from the training set, used to evaluate a model during training. It provides an intermittent check on the model's performance, allowing for hyperparameter tuning and model selection. By evaluating model performance on a validation set, one can detect issues like overfitting (where the model performs exceptionally well on the training set but poorly on new, unseen data). Once the model is optimized using the validation set, its final performance is then assessed on the test set.
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.

Appendix B. Example Data Sheet - Commercial Sensor

OVERVIEW	35
Compliance and Certifications	35
Description	35
Features	35
Use Cases	35
MODEL CHARACTERISTICS	36
Software Flow Diagram	37
Dataset Nutrition Label	38
IoT Security and Privacy Label	39
Machine Learning Model Specification	41
Person Detection Model	41
Face Identification Model	41
Performance Analysis	43
Environmental Sensitivity	44
Demographic biases	44
HARDWARE	45
Hardware Details	46
I2C Protocol	47
Device Diagrams	48
Bill of Materials	50
Environmental Impact	51
Acronyms	52
Glossary	53

OVERVIEW

Person Sensor V1.0

SEN-21231

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. The sensor has been audited by Kodelski Security for security and privacy implications.

Description

The Person Sensor is a small, low-cost hardware module that detects nearby peoples' faces, and returns information about how many there are, where they are relative to the device, and performs facial recognition. It is designed to be used as an input to a larger system, for example to wake up a kiosk display from sleep mode when somebody approaches, mute a microphone when nobody is present, or orient a fan so it's always pointing at the nearest person.

The sensor has a small form factor and utilizes a monochrome camera with a field of view of 640 x 480 (VGA). The input voltage for the sensor is 3.3V and 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 at 400 kb/s. Longer cables can be used at lower data rates. The sensor has a maximum data rate of 400 kb/s.

Features

- Real-time person + head pose tracking with on-device ML
- Real-time person identification with on-device ML
- Low power consumption
- Onboard camera
- Small form factor: 22 x 20 x 10 mm
- I2C serial communication
- Lead-free

Use Cases

- Security
- Home automation
- Consumer appliances

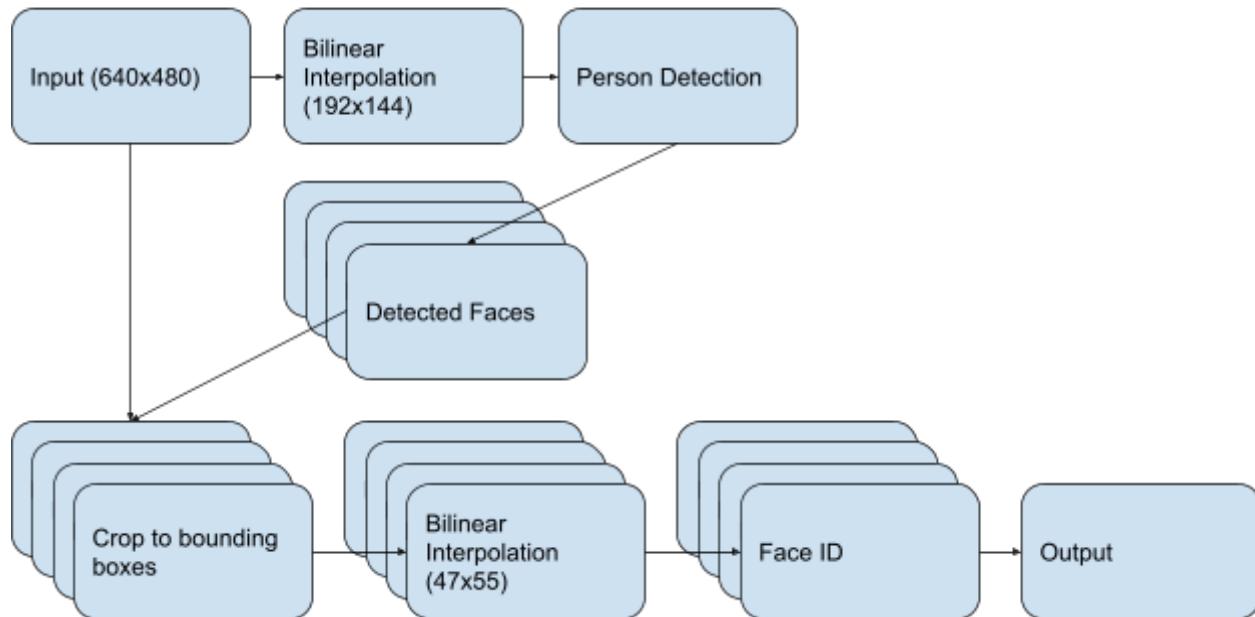
MODEL CHARACTERISTICS

Software Flow Diagram

8-bit grayscale images (640x480) are resized to 192x144 and passed into a RetinaFace model trained to detect human faces. This model outputs a list of faces with coordinates for a bounding box around each face as well as five key facial landmarks. If identity is enabled, bounded faces are cropped out of the original image and rescaled to 47x55 and passed into a DeepID model to generate an embedding. This embedding is compared with saved facial IDs, and the nearest ID is returned along with the bounding box and information about whether the person is facing the sensor. Output information is communicated via Qwiic interface to the application processor.

	Person Detection Model	Person ID Model
Architecture	RetinaFace	DeepID
Framework	TFLite Micro	TFLite Micro
Validation Set	20%	-
Quantization	int8	int8
Inference Time	140 ms	125 ms
Peak RAM Usage	442.6 kB	189 kB
Flash Usage	449 kB	397 kB

Person Sensor Software Flow



Dataset Nutrition Label

The data nutrition label is publicly available [here](#), with some important features outlined below.

At a Glance

About humans	Upstream sources	Technical review	Ethical review	Update frequency
Yes	No	Unsure	No	No

Intended Use

- **Intended Domain.** Face Detection and Landmark Detection
- **Intended Use.** Face Detection and Landmark Detection

Known Uses

Restrictions on Use

- no

Do Not Use

- **Domain.** Military

General risks
Any additional risks?

Individual Information
no

Consent
Yes.

Generalized Inferences
Most face image sources and existing datasets over-represent people in developed countries. Since this dataset contains images available on the internet, it probably suffers a similar bias.

Generalized Inferences - Mitigation

Sensitive Content
Not Applicable

Documented Known Issues

Other Known Issues

Number of issues

Risky	0
Safe	3
Unknown	4

IoT Security and Privacy Label

Security & Privacy Overview

Useful Sensors

Person Sensor V1.0

Firmware version: Not disclosed - updated on: 2023-05-03

The device was manufactured in: China

 Data Practices	Security updates	No security updates	(i)	+ (grey)
	Access control	Not disclosed	(i)	
	Sensor data collection	 Visual	 Audio	 Physiological
	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	(i)	
	Detailed Security & Privacy Label: Not disclosed			
More Information				
	CMU IoT Security and Privacy Label CISPL 1.0 iotsecurityprivacy.org			

Security & Privacy Details

Useful Sensors

Person Sensor V1.0

Firmware version: Not disclosed - updated on: 2023-05-03

The device was manufactured in: China

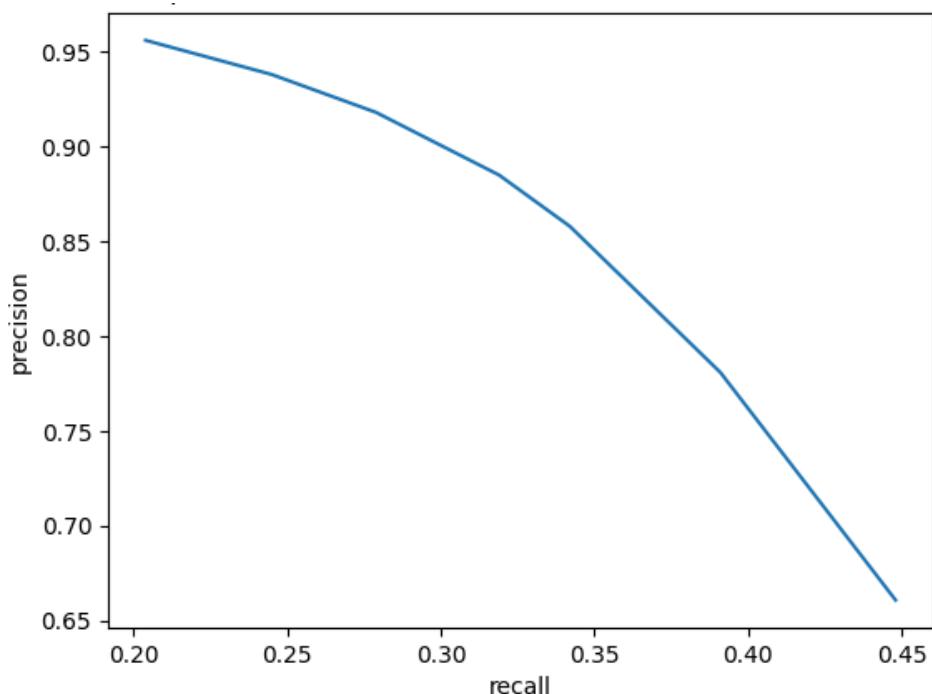
 Security Mechanisms	Security updates	No security updates <small> ⓘ Sensor is a standalone unit. For security and privacy, the firmware cannot be changed and only sensor outputs are available.</small>
	Access control	Not disclosed <small> ⓘ </small>
	Security oversight	Audits performed by third-party security auditors <small> ⓘ Third party security audit performed by Kudelski Security</small>
	Ports and protocols	Not disclosed <small> ⓘ </small>
	Hardware safety	Not disclosed <small> ⓘ </small>
	Software safety	Not disclosed <small> ⓘ </small>
	Personal safety	Not disclosed <small> ⓘ </small>
	Vulnerability disclosure and management	Not disclosed <small> ⓘ </small>
	Software and hardware composition list	Not disclosed <small> ⓘ </small>
	Encryption and key management	Not disclosed <small> ⓘ </small>
 Data Practices	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
 More Information	Data sold to	Not sold
	Other collected data	None
	Data linkage	Not disclosed <small> ⓘ </small>
	What will be inferred from User's Data	Not disclosed <small> ⓘ </small>
	Special data handling practices for children	Not disclosed <small> ⓘ </small>
	In Compliance with	Not disclosed <small> ⓘ </small>
	Privacy policy	Not disclosed <small> ⓘ </small>
	Call Useful Sensors with your questions at	1 805 813 7571 <small> ⓘ </small>
	Email Useful Sensors with your questions at	contact@usefulsensors.com <small> ⓘ </small>
	Functionality when offline	Full functionality on offline mode <small> ⓘ </small>
Functionality with no data processing		
Physical actuations and triggers		
Compatible platforms		

CMU IoT Security and Privacy Label CISPL 1.0 iotsecurityprivacy.org

Machine Learning Model Specification

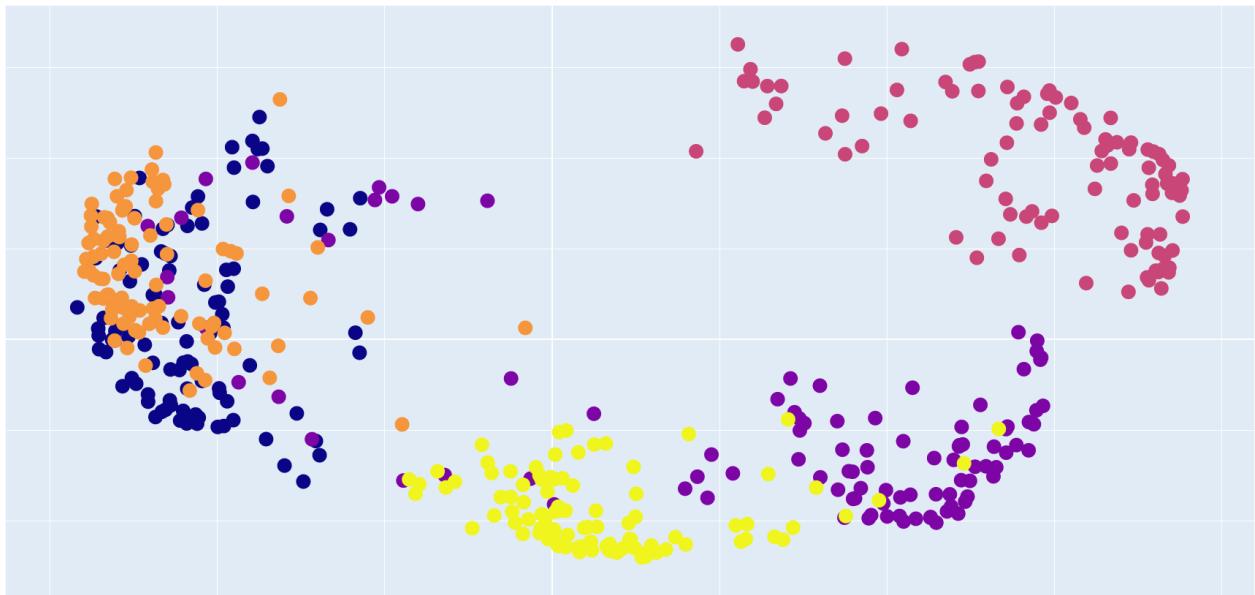
Person Detection Model

The person detection model was trained on a proprietary dataset of ~30,000 images with 300k labeled faces and five facial landmarks per face. The model input is a 192x144 raw image in 8-bit grayscale format, equivalent to 27,648 features. The training process was performed until the model accuracy ceased to improve. Final model performance achieved a precision of 91.8% on the test set, using a threshold of 0.7. The precision-recall curve of the model on the test set is shown below. The model was quantized to 8-bit integer using post training quantization using the Tensorflow Lite converter and is deployed using the Tensorflow Lite Micro runtime.



Face Identification Model

The face identification model was fine-tuned on a proprietary dataset encompassing ~4000 images across 5 identities captured using the sensor camera module. The input to the model is a 47x55 raw image in 8-bit grayscale format, equivalent to 2,585 features. To produce the best separation between faces a dense classification layer was added to the model, and several iterations of freezing either the classification layer or the model was used to achieve a higher accuracy on the fine-tuning dataset. Finally, the classification layer was removed and embedding separation was evaluated using Principal Component Analysis (PCA) in three dimensions.



Each color represents one of five unique identities in the validation dataset. Distances between points indicate approximate distances between embeddings simplified to 2-D space.

The model was quantized to 8-bit integer using post training quantization using the Tensorflow Lite converter and is deployed using the Tensorflow Lite Micro runtime. On the sensor, the embedding generated by the Face ID model is compared against registered faces, and if a face with similar enough features is found, that identity is used. Otherwise, an identity of -1 is returned to indicate that no registered identity was found.

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.

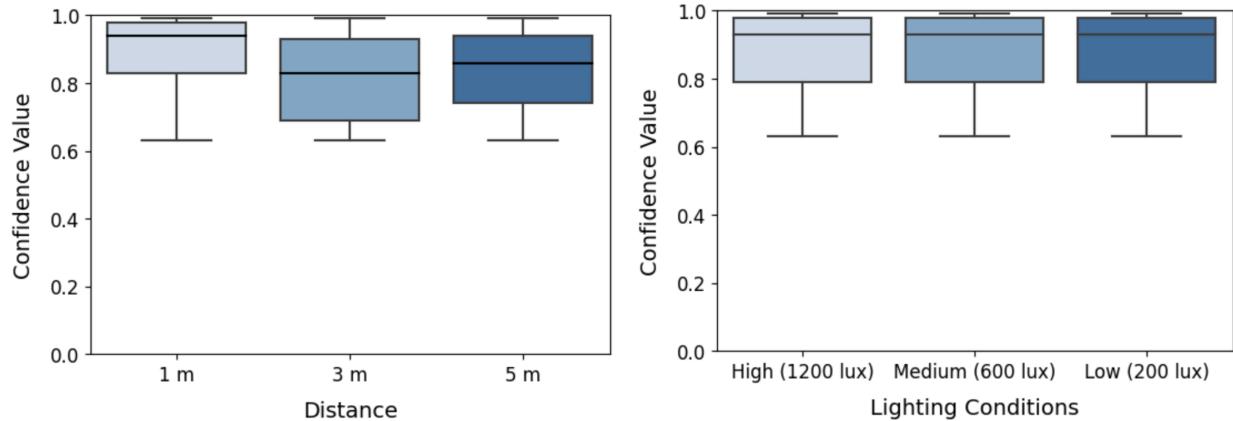
The lighting levels were controlled using a dimmer switch that had three levels of operation, corresponding to 208 ± 31 , 584 ± 51 , and 1149 ± 59 lux, respectively. When the lights were turned off, the illuminance meter gave a reading of zero lux. When all the lights were turned on at full strength, 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.

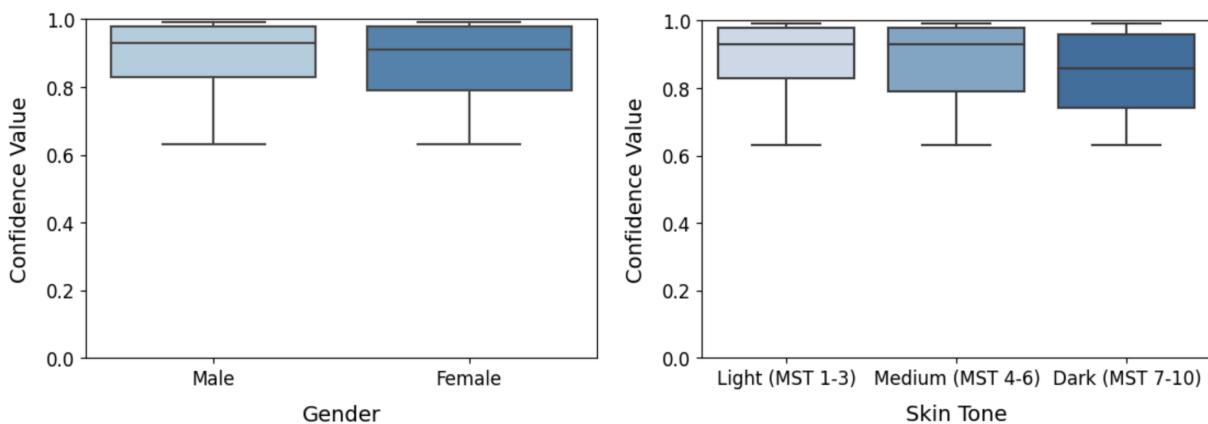
Environmental Sensitivity

The device showed no decrease in performance under decreased lighting conditions. A moderate drop off in performance of around 10% is observed at distances 3-5 meters from the sensor.



Demographic biases

A small gender bias is observed in model performance. A moderate skin tone bias was observed, showing approximately a 10% decrease in the confidence value for individuals with a darker skin tone.



HARDWARE

Hardware Details

Camera Specifications (see here)	
Field of view (horizontal)	110°
Color Filter Array	Bayer, Monochrome
Frame Rate	60FPS @ 48MHz
Pixel Array (Active/ Effective)	644 x 484 / 640x480
Electrical Specifications	
Operating Voltage Range (regulator enabled)	3.1V to 3.5V
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	Text on sensor is upright, up arrow points upwards
GPIO mode	INT pin is high when person is detected
Diagnostic LED	Default behavior of green LED on board: illuminates when person detected.
Data Transfer and Format	See I2C Protocol Table
I2C Address	0x63

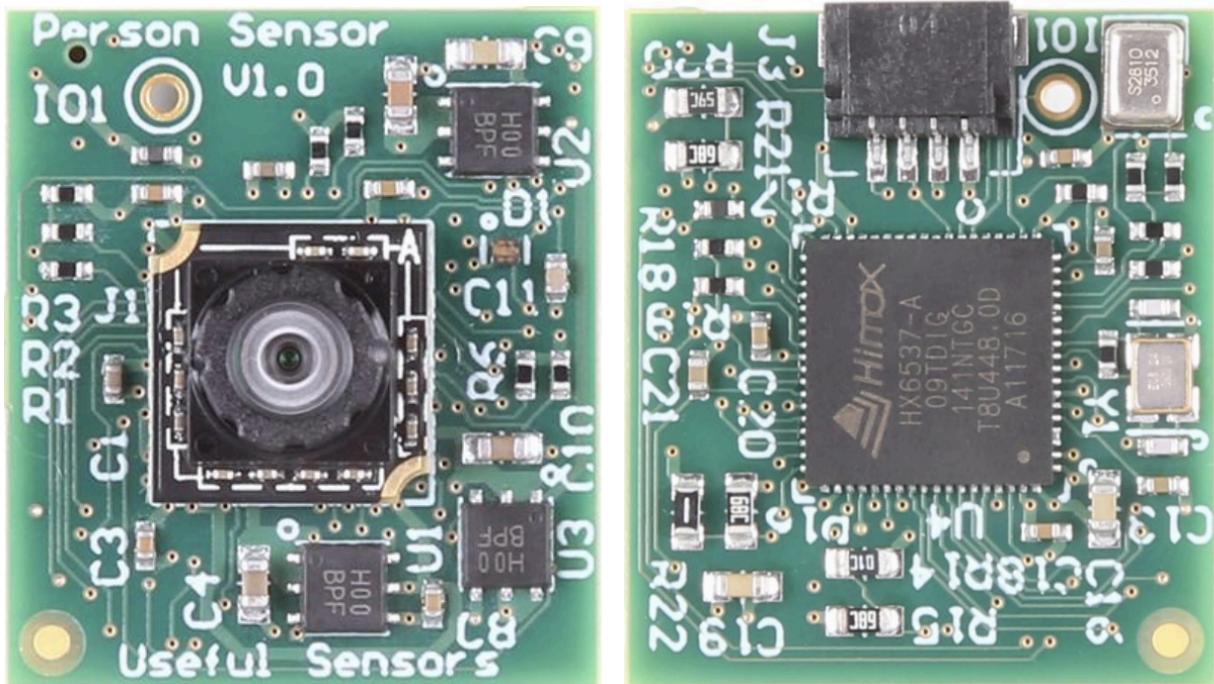
I2C Protocol

Address	Name	Default	Description
0x01	Mode	0x01 (continuous)	Mode. See mode table below.
0x02	Enable ID	0x00 (False)	Enable / Disable the ID model. With this flag set to False, only capture bounding boxes.
0x03	Single shot	0x00	Trigger a single-shot inference. Only works if the sensor is in standby mode.
0x04	Label next ID	0x00	Calibrate the next identified frame as person N, from 0 to 7. If two frames pass with no person, this label is discarded.
0x05	Persist IDs	0x01 (True)	Store any recognized IDs even when unpowered.
0x06	Erase IDs	0x0	Wipe any recognized IDs from storage.
0x07	Debug Mode	0x01 (True)	Whether to enable the LED indicator on the sensor.

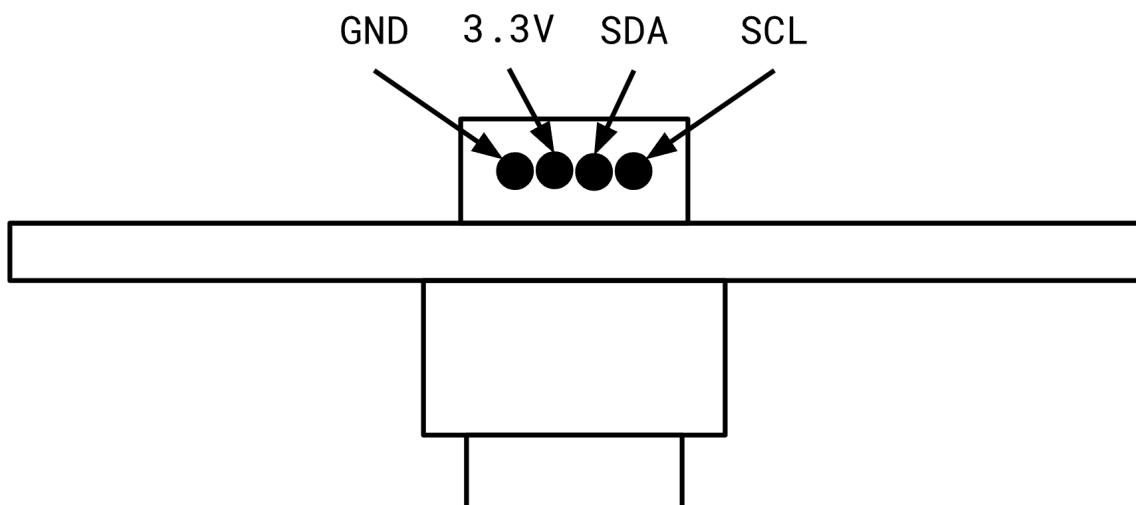
Mode	Name	Description
0x00	Standby	Lowest power mode, sensor is in standby and not capturing.
0x01	Continuous	Capture continuously, setting the GPIO trigger pin to high if a face is detected.

Device Diagrams

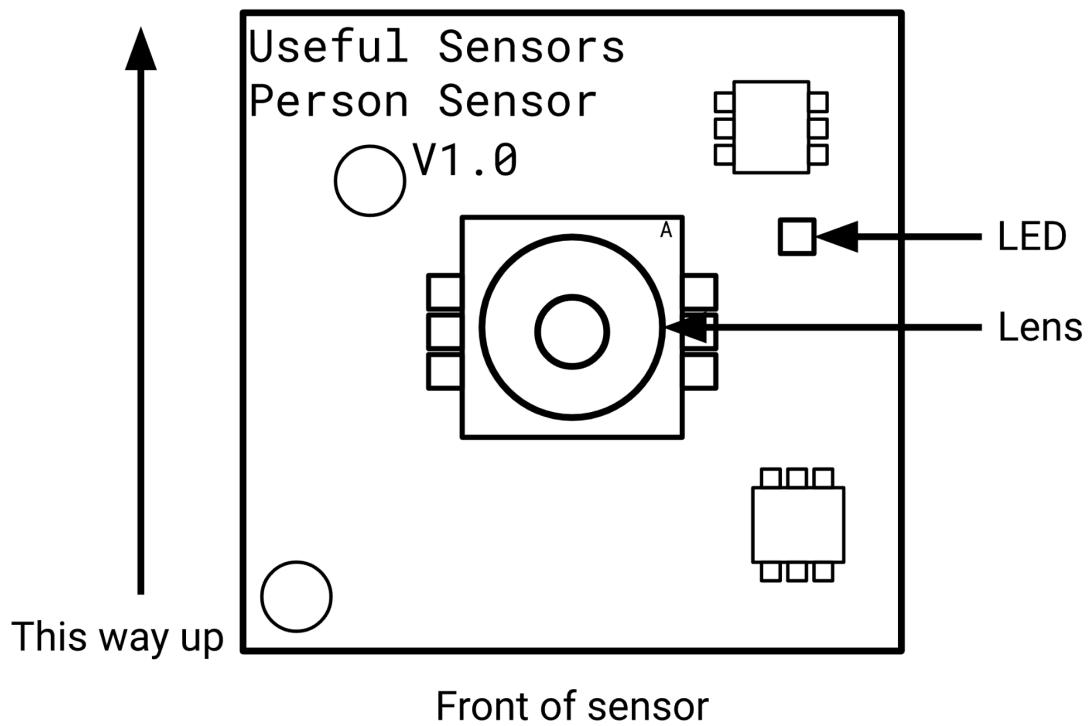
Front and backside of the sensor module.



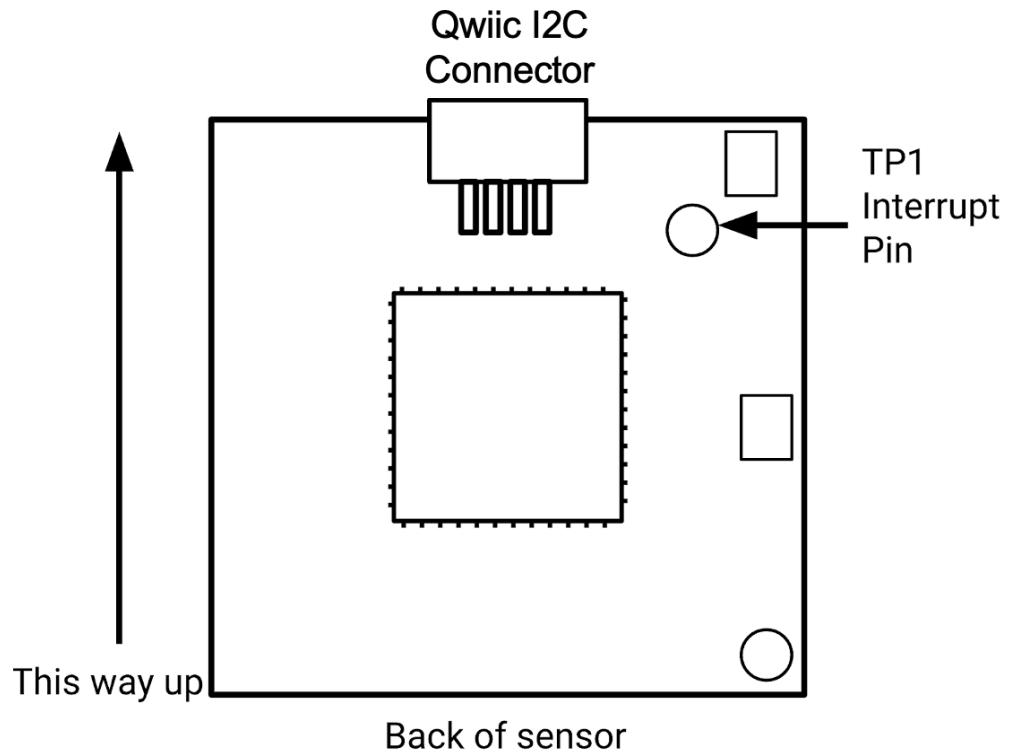
Qwiic connector interface.



Frontside schematic of sensor.



Backside schematic of sensor.



Bill of Materials

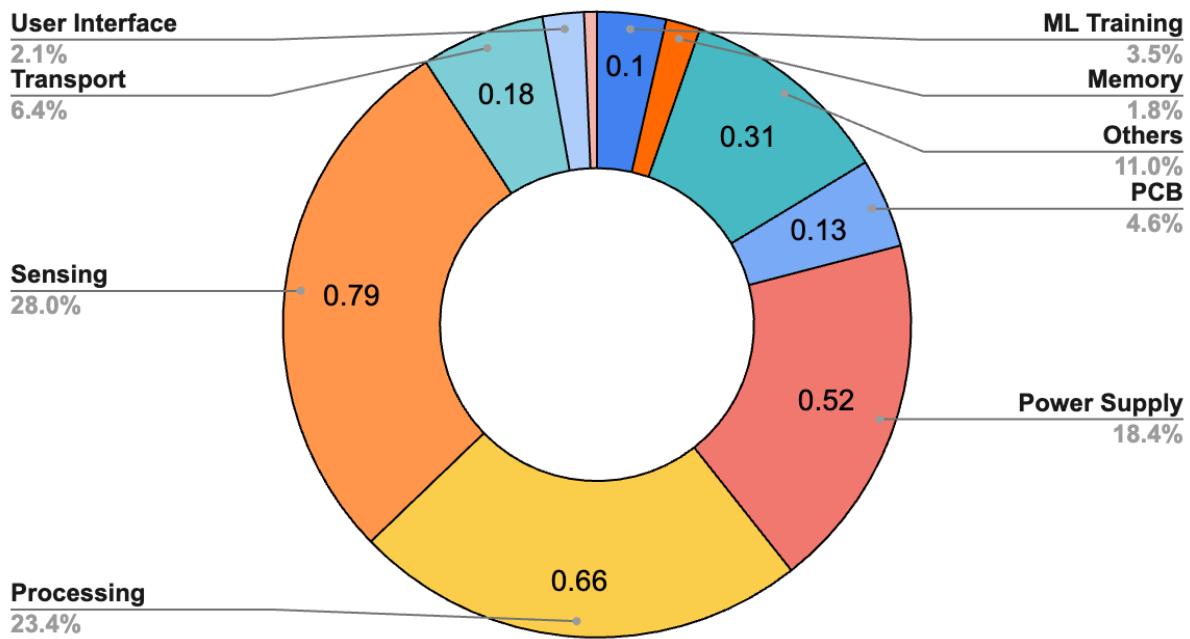
The following is a comprehensive list of materials required to assemble the Person Sensor V1.0. All unit cost values quoted in minimum order quantity of one.

Category In TinyML Calculator	Component	Unit Cost (\$)	Quantity	Manufacturer	Link to Datasheet (if available)
Functional Components					
✓	Himax MCU HX6537/39/40-A	14.50	1	HiMax	https://cdn.sparkfun.com/assets/6/6/7/e/8/HX6537-A_DS_public_v01_1.pdf
✓	Camera Module HM0360-MWA	8.81	1	HiMax	https://cdn.sparkfun.com/assets/d/2/9/9/7/Pre-HM0360_DS_preliminary_v04_Ltd. -1.pdf
✓	MEMS Microphone SPH0641LM4H-1	1.05	1	Knowles	https://media.digikey.com/pdf/Data%20Sheets/Knowles%20Acoustics%20PDFs/SPH0641LM4H-1.pdf
✓	Crystal Oscillator ECS-240-10-36-CKM-TR	0.57	1	ECS Inc.	https://ecsxtal.com/store/pdf/ECX-2236.pdf
Power Circuitry					
	Adjustable Linear Voltage Regulator R1173D001B-TR-FE	1.33	3	Nisshinbo Micro Devices Inc.	https://www.nisshinbo-microdevices.co.jp/en/pdf/datasheet/r1173-ea.pdf
Indication					
✓	RGB LED	0.1	1	Harvatek Corporation	https://media.digikey.com/pdf/Data%20Sheets/Harvatek%20PDFs/B39D3RGB-F6C0001HOU1930.pdf
Connectors					
	Board to Camera OK-10F030-04	1.22	1	AliExpress	N/A
	Qwiic JST SH 4-pin Right Angle Connector	0.40	1	Adafruit	N/A
Passive Components					
✓	Misc resistors	0.01	15	-	N/A
✓	Misc capacitors	0.01	17	-	N/A
✓	Misc inductors	0.01	1	-	N/A
	Total	30.97			

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 8 out of 11 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 **2.82 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
GDPR	General Data Protection Regulation
GPIO	General Purpose Input Output
ML	Machine Learning
I2C	Inter-Integrated Circuit
ID	Identifier
IoU	Intersection Over Union
LED	Light-Emitting Diode
MCU	Microcontroller Unit
MEMS	Microelectromechanical System
MST	Monk Skin Tone Scale
PCA	Principal Component Analysis
RGB	Red Blue Green

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.
IoU	Intersection Over Union (IoU) is a metric used to evaluate the accuracy of an object detector on a specific dataset. It measures the overlap between the predicted bounding box (from the detector) and the ground truth bounding box. Values range between 0 and 1, where a higher value indicates better prediction accuracy. A value of 0 indicates no overlap, while a value of 1 indicates perfect overlap (the predicted box matches the ground truth exactly).
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.
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.
Principal Component Analysis	A statistical procedure that transforms a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. These components are orthogonal to each other and capture the variance in the data in decreasing order.
Monk Skin Tone Scale	A 10-shade system, developed by Google, designed to provide a more inclusive representation of diverse skin tones in image-based technologies to address the challenges of representation in image-based technologies, especially for people of color.
Training Set	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.
Test Set	A subset of the dataset that is strictly used to evaluate the performance of a model after it has been trained. The test set provides an unbiased evaluation of a model's generalization to new, unseen data. It should never be used during training or hyperparameter tuning.
Validation Set	A subset of the dataset, separate from the training set, used to evaluate a model during training. It provides an intermittent check on the model's performance, allowing for hyperparameter tuning and model selection. By evaluating model performance on a validation set, one can detect issues like overfitting (where the model performs exceptionally well on the training set but poorly on new, unseen data). Once the model is optimized using the validation set, its final performance is then assessed on the test set.
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.

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