

SciTinyML – ICTP Workshop

Scientific Use of Machine Learning on Low Power Devices

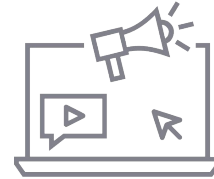
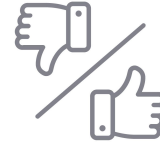
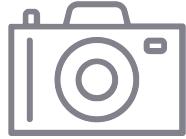
Machine Learning Sensors

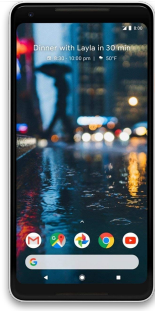
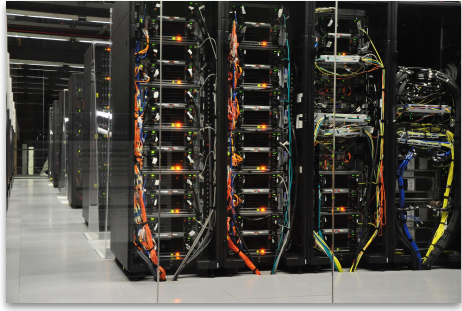
Acknowledgements: Z. Asgar, C. Banbury, B. Brown, E. Chen, J. MacArthur, B. Plancher, S. Prakash, S. Katti, V. J. Reddi, P. Warden & the Useful Sensors Team

*Matthew Stewart, Ph. D. | Postdoctoral Researcher |
John A. Paulson School of Engineering and Applied Sciences | Harvard University |
Web: <https://mpstewart.io>*



Applications of Machine Learning





No Good Data Left Behind

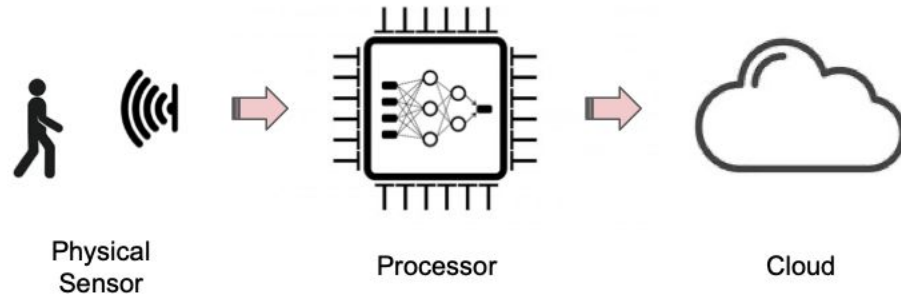
5 Quintillion

bytes of data produced
every day by IoT

<1%

of unstructured data is
analyzed or used at all

The “Classic” TinyML Paradigm



Sensor 1.0

Is Your TV Watching You? How? x +

avast.com/c-smart-tv-spying-on-you

TinyML Harvard MLC Seed Meta \$\$\$ TimeBuddy Geo Chart Exampl... CS249r

Academy

Avast Academy > Security > Internet of Things > How to Stop Your Smart TV From Spying on You

INTERNET OF THINGS

How to Stop Your Smart TV From Spying on You

FBI warns about snoopy smart x +

zdnet.com/article/fbi-warns-about-snoopy-smart-t...

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2D NET tomorrow belongs to those who embrace it today

/ innovation Home / Innovation / Security

FBI warns about snoopy smart TVs spying on you

An FBI branch office warns smart TV users that they can be gateways for hackers to come into your home. Meanwhile, the smart TV OEMs are already spying on you.

Written by Steven Vaughan-Nichols, Senior Contributing Editor on Dec. 3, 2019

Google Calls Hidden Microphone in Its Nest Home Security Devices an 'Error'

popularmechanics.com/technology/security/a2644...

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POPULAR MECHANICS HOME NEW TECH SCIENCE MILITARY POP MECH PRO SUBSCRIBE SIGN IN

New Technology > Security

Google Calls Hidden Microphone in Its Nest Home Security Devices an 'Error'

The company says its was an oversight, but it does little to stem paranoia.

BY SAM BLUM PUBLISHED: FEB 21, 2019



2021 EDITORS' CHOICE

2021 Editors' choice

tech frontier

How to stop your smart home x +

theguardian.com/technology/2020/mar/08/how-to-...

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How to stop your smart home spying on you

Everything in your smart home, from the lightbulbs to the thermostat, could be recording you or collecting data about

Most viewed

Bryan Adams: 'My doc says men need sex 27 times a month, but who gets that?'

Attacks on Pacific north-west power stations raise

How do we architect future Tiny Machine Learning (tinyML) sensors *efficiently*, *effectively* and *robustly* into the embedded ecosystem?

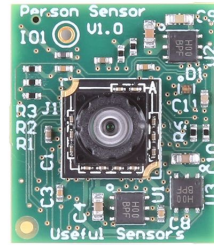
Machine Learning Sensors

“

An ML sensor is a **self-contained system** that utilizes **on-device machine learning** to extract **useful information** by observing some complex set of phenomena in the **physical world** and reports it through a **simple interface** to a wider system.

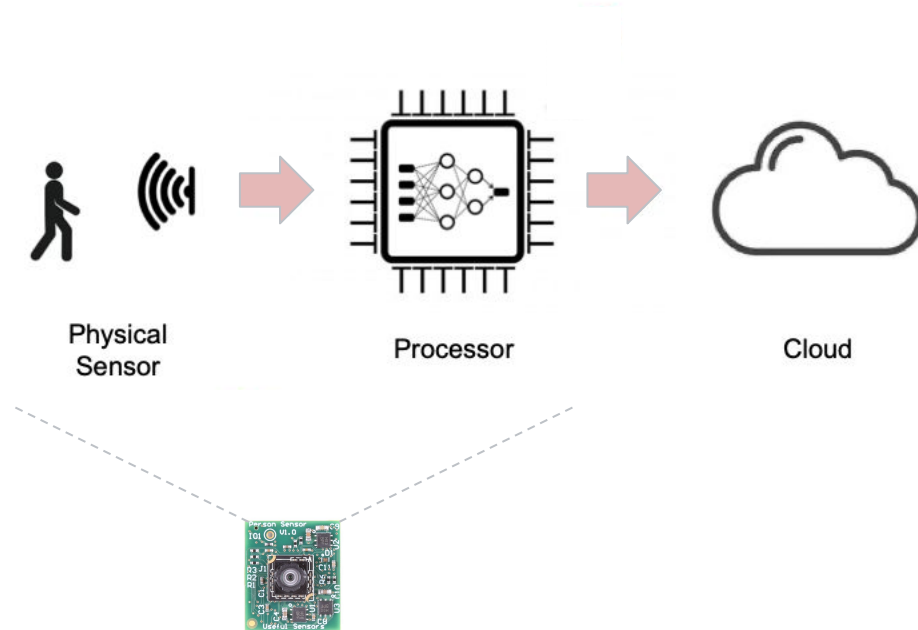
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Machine Learning Sensors

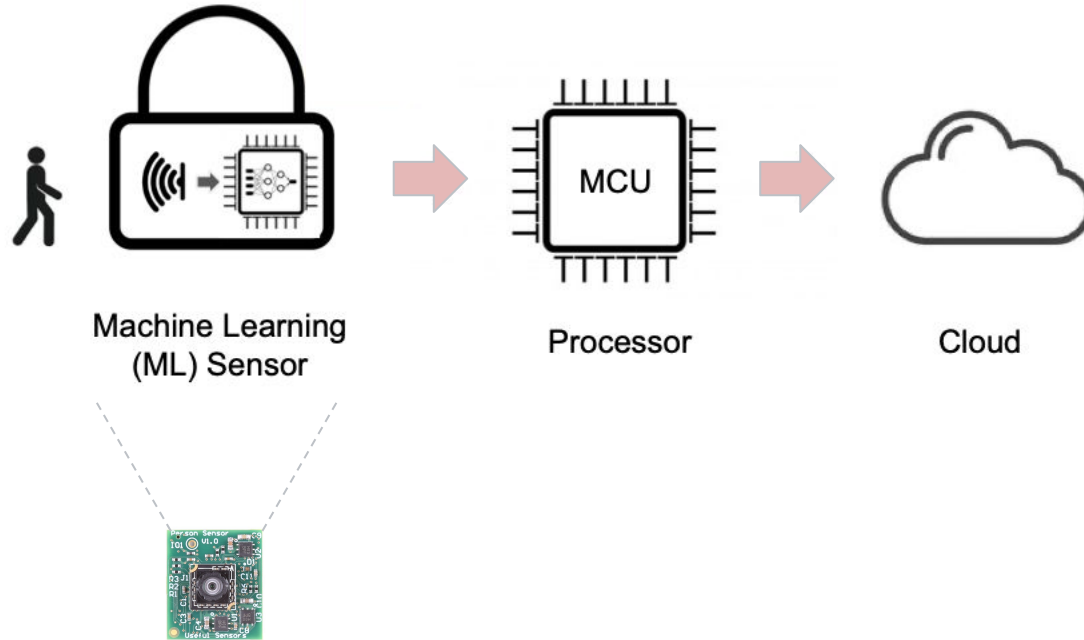


by Useful Sensors

Machine Learning Sensors



Machine Learning Sensors



Sensor 2.0

ML Sensors - Guiding Set of Principles

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
















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The screenshot displays the Digi-Key website's search results for 'temperature sensor'. The page features a navigation bar with the Digi-Key logo, a search bar containing 'temperature sensor', and a shopping cart icon showing '0 item(s)'. Below the navigation bar, the breadcrumb trail reads 'Product Index > Sensors, Transducers > Temperature Sensors - Analog and Digital Output'. The main heading is 'Temperature Sensors - Analog and Digital Output', with a search bar showing 'Search Within' and 'Results: 3,131'. The page is organized into several filter columns: Manufacturer, Series, Packaging, Product Status, Sensor Type, Sensing Temperature - Local, Sensing Temperature - Remote, Output Type, Voltage - Supply, and Resolution. Each filter column contains a search bar and a list of options. Below the filter columns, there are sections for 'Stocking Options', 'Environmental Options', 'Media', and 'Marketplace Product'. The 'Marketplace Product' section includes an 'Apply All' button and '3,131 Results'. At the bottom, there is a 'SEARCH ENTRY' field containing 'temperature sensor' and a 'Showing 1 - 25 of 3,131' indicator.

Compare	Mfr Part #	Quantity Available	Price	Series	Package	Product Status	Sensor Type	Sensing Temperature - Local	Sensing Temperature - Remote	Output Type	Voltage - Supply	Resolution	Features	Accuracy - Highest (Lowest)	Test Condition
<input type="checkbox"/>	 TMP236A2DBZT SENSOR TEMPERATURE Texas Instruments	1,053 In Stock	1: \$1.49000 Cut Tape (CT) 250: \$0.71800 Tape & Reel (TR)	-	Tape & Reel (TR)  Cut Tape (CT)  Digi-Reel® 	Active	Analog, Local	-10°C ~ 125°C	-	Ratiometric, Voltage	3.1V ~ 5.5V	19.5mV/°C	-	±2°C	-10°C ~ 125°C
<input type="checkbox"/>	 TMP236A4DCKT SENSOR TEMPERATURE Texas Instruments	1,678 In Stock	1: \$1.24000 Cut Tape (CT) 250: \$0.59800 Tape & Reel (TR)	-	Tape & Reel (TR)  Cut Tape (CT)  Digi-Reel® 	Active	Analog, Local	-10°C ~ 125°C	-	Ratiometric, Voltage	3.1V ~ 5.5V	19.5mV/°C	-	±4°C	-10°C ~ 125°C
<input type="checkbox"/>	 TMP236A2DCKT SENSOR TEMPERATURE Texas Instruments	2,307 In Stock	1: \$1.41000 Cut Tape (CT) 250: \$0.67800 Tape & Reel (TR)	-	Tape & Reel (TR)  Cut Tape (CT)  Digi-Reel® 	Active	Analog, Local	-10°C ~ 125°C	-	Ratiometric, Voltage	3.1V ~ 5.5V	19.5mV/°C	-	±2°C	-10°C ~ 125°C
<input type="checkbox"/>	 TMP451JQDFQ1 SENSOR TEMPERATURE Texas Instruments	340 In Stock	1: \$2.06000 Cut Tape (CT) 250: \$1.02860 Tape & Reel (TR)	Automotive, AEC-Q100	Tape & Reel (TR)  Cut Tape (CT)  Digi-Reel® 	Active	Digital, Local/Remote	-40°C ~ 125°C	-64°C ~ 191°C	PC/SMBus	1.7V ~ 3.6V	12 b	One-Shot, Output Switch, Programmable Limit, Shutdown Mode	±1°C (±2°C)	0°C ~ 70°C (-40°C ~ 125°C)
<input type="checkbox"/>	 TMP236A4DBZT SENSOR TEMPERATURE Texas Instruments	596 In Stock	1: \$1.32000 Cut Tape (CT) 250: \$0.63800 Tape & Reel (TR)	-	Tape & Reel (TR)  Cut Tape (CT)  Digi-Reel® 	Active	Analog, Local	-10°C ~ 125°C	-	Ratiometric, Voltage	3.1V ~ 5.5V	19.5mV/°C	-	±4°C	-10°C ~ 125°C
<input type="checkbox"/>	 TMP451HQDFQ1 SENSOR TEMPERATURE Texas Instruments	227 In Stock 3,250 Factory 	1: \$2.06000 Cut Tape (CT) 250: \$1.02860 Tape & Reel (TR)	Automotive, AEC-Q100	Tape & Reel (TR)  Cut Tape (CT)  Digi-Reel® 	Active	Digital, Local/Remote	-40°C ~ 125°C	-64°C ~ 191°C	PC/SMBus	1.7V ~ 3.6V	12 b	One-Shot, Output Switch, Programmable Limit, Shutdown Mode	±1°C (±2°C)	0°C ~ 70°C (-40°C ~ 125°C)
<input type="checkbox"/>	 TMP461AIRUNT-S TEMPERATURE SENSOR Texas Instruments	9,073 In Stock 10,000 Factory 	1: \$2.56000 Cut Tape (CT) 250: \$1.28020 Tape & Reel (TR)	-	Tape & Reel (TR)  Cut Tape (CT)  Digi-Reel® 	Active	Digital, Local/Remote	-40°C ~ 125°C	-64°C ~ 191°C	SMBus	1.7V ~ 3.6V	11 b	One-Shot, Output Switch, Programmable Limit, Shutdown Mode, Standby Mode	±1°C (±1.25°C)	-10°C ~ 100°C (-40°C ~ 125°C)
<input type="checkbox"/>	 TMP12FP ANALOG TEMPERATURE SENSOR Analog Devices Inc.	1,253 Marketplace	108: \$2.79000 Bulk	-	Bulk 	Active	Digital, Local	-40°C ~ 125°C	-	SPI	2.7V ~ 5.5V	12 b	One-Shot, Shutdown Mode	±2°C (±2.5°C)	-25°C ~ 85°C (-40°C ~ 125°C)
<input type="checkbox"/>	 MAX6630MUT-T DIGITAL TEMPERATURE SENSOR Analog Devices Inc./Maxim Integrated	3,396 Marketplace	110: \$2.75000 Bulk	-	Bulk 	Active	Digital, Local	-55°C ~ 125°C	-	SPI	3V ~ 5.5V	12 b	Shutdown Mode	±0.8°C (-5°C, 6.5°C)	25°C (150°C)
<input type="checkbox"/>	 TMP35FT9 ANALOG TEMPERATURE SENSOR Analog Devices Inc.	20,365 Marketplace	298: \$1.01000 Bulk	Automotive	Bulk 	Active	Analog, Local	10°C ~ 125°C	-	Analog Voltage	2.7V ~ 5.5V	10mV/°C	Shutdown Mode	±2°C (±3°C)	25°C (10°C ~ 125°C)
<input type="checkbox"/>	 MAX6629MUT-T DIGITAL TEMPERATURE SENSOR Analog Devices Inc./Maxim Integrated	9,848 Marketplace	139: \$2.17000 Bulk	-	Bulk 	Active	Digital, Local	-55°C ~ 125°C	-	SPI	3V ~ 5.5V	12 b	Shutdown Mode	±0.8°C (-5°C, 6.5°C)	25°C (150°C)
<input type="checkbox"/>	 AD22103KR-REEL	2,350 Marketplace	289: \$1.04000 Bulk	AD22103	Bulk 	Active	Analog, Local	0°C ~ 100°C	-	Analog	2.7V ~ 3.6V	28mV/°C	-	±2°C (±2.5°C)	25°C (0°C ~

 Feedback

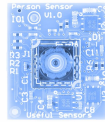
 Need Help?

ML Sensors – Guiding Set of Principles

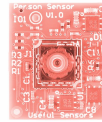
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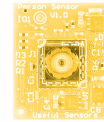
Person detector



Gaze sensor



Voice command



Text recognizer



...



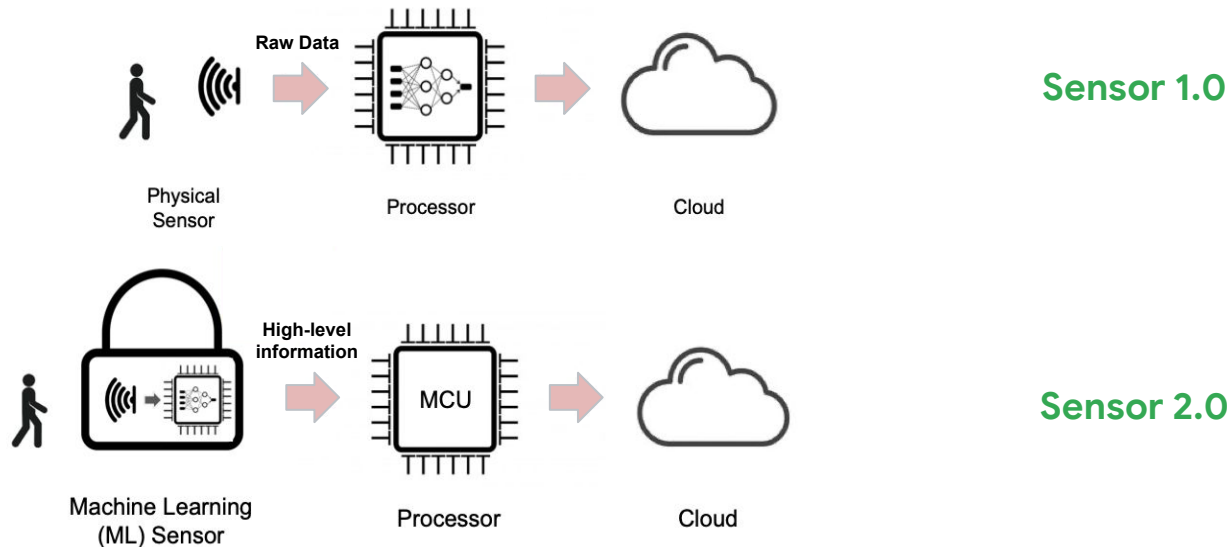
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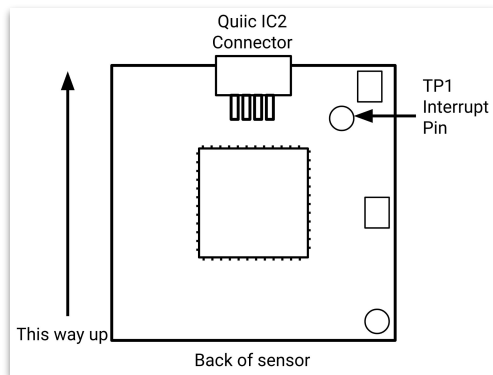


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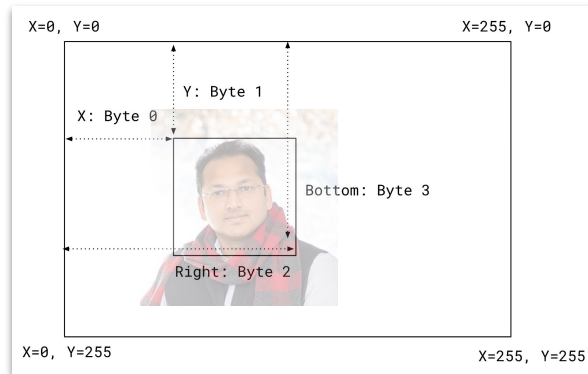
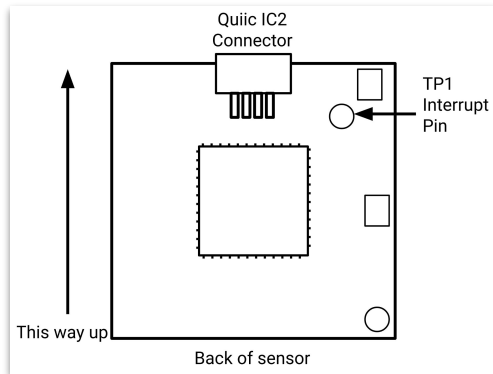
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We need to define or rely on standard interfaces and mechanisms for communication with sensors.

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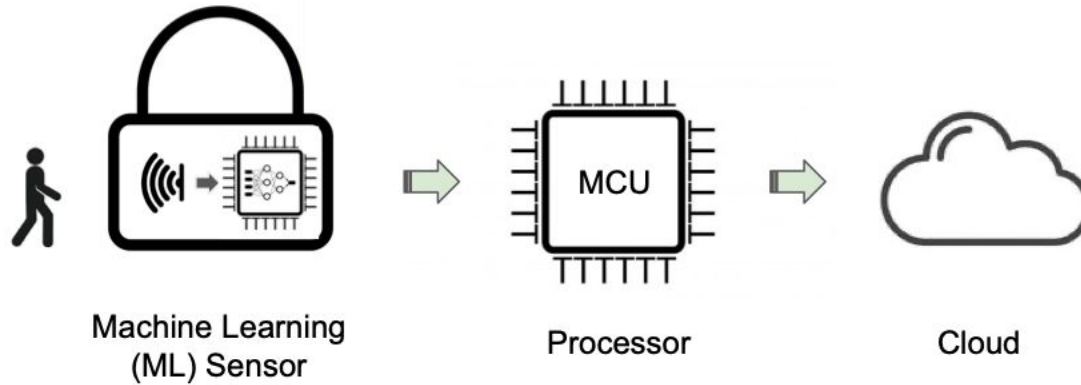


We need to define data formats to enable interoperability and exchange of ML sensors across manufacturers

ML Sensors - Guiding Set of Principles

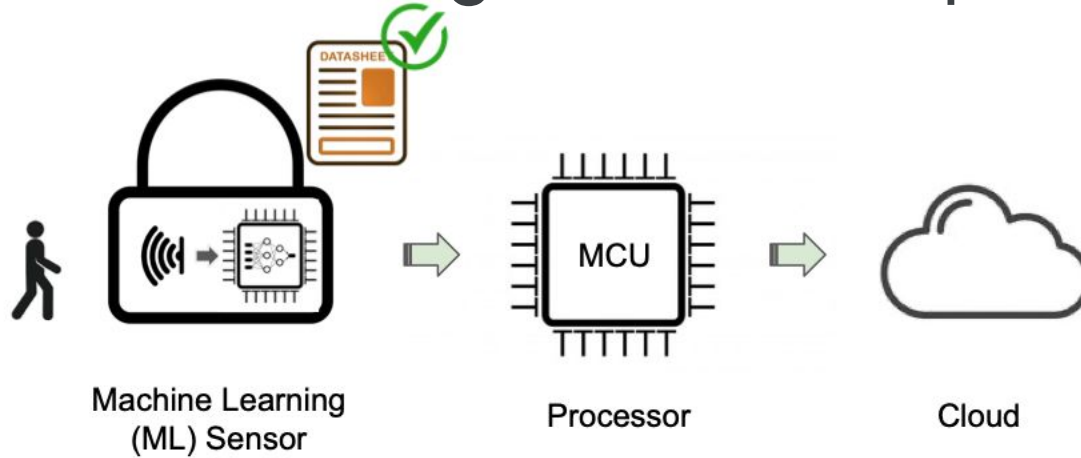
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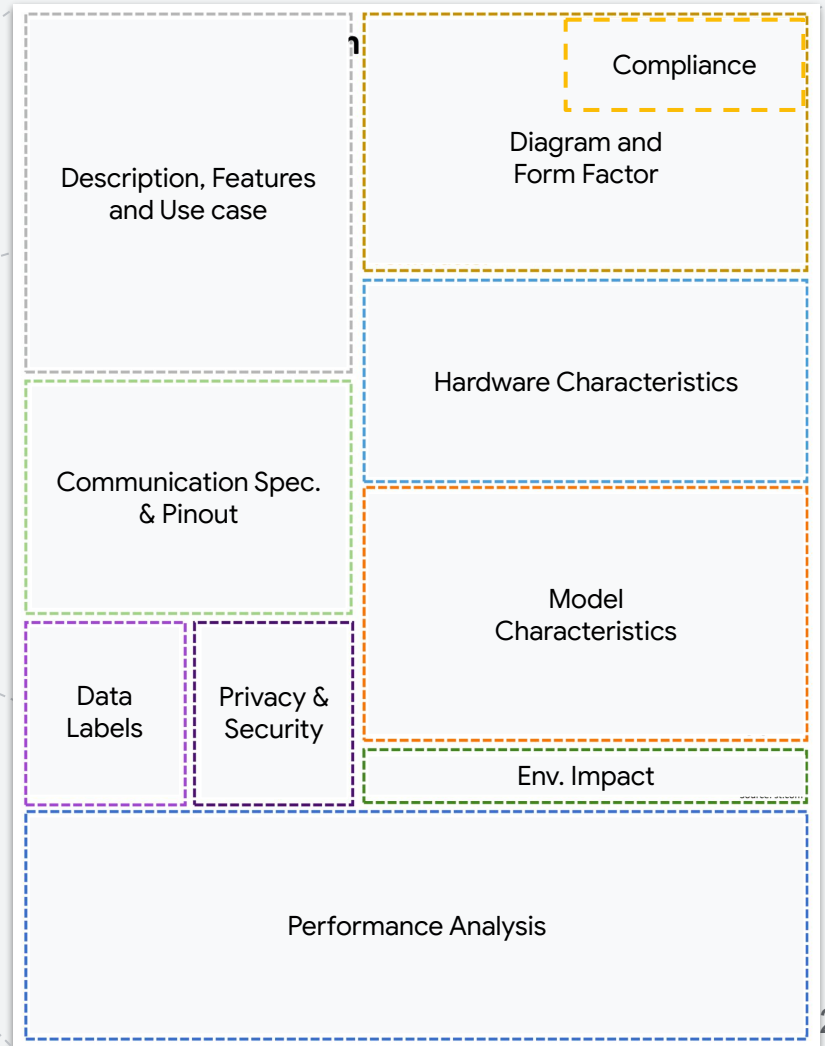
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E.g. ML Sensors Datasheets



E.g. ML Sensors Datasheets



PA1 Person Detection Module

Description: The PA1 Person Detection Module enables you to quickly and easily add smarts to your IoT deployment to monitor and detect for humans. You can use this module indoors and outdoors to understand where and when humans arrive at your deployment site.

Features:

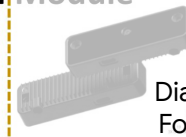
- Real-time Person Detection with On-Device ML
- Finds a person at a maximum distance of 10 meters to a minimum distance of 1 meter
- Operates in a wide range of light conditions (20000 Lux)
- Operates in a wide temperature range (0 to 50 °C)
- Features Color and Black-and-White Detection Modules

Use Cases:

- Smart business and home security systems
- Multi-modal key word spotting for virtual assistants
- Occupancy sensors and other infrastructure sensors

Description, Features, and Use Cases

Module



Source: docs.luxonis.com

Diagram and Form Factor

Diagrams and Form Factor



Sources: fabacademy.org, electrochematics.com, and nxp.com/docs

Pin	Function	Pin	Function
(+) VCC	C1	14	GND I-1
Pin 10	C2	13	Pin 0 (Analog input 0, AREF)
Pin 9	C3	12	Pin 1 (Analog input 1)
Reset	C4	11	Pin 2 (Analog input 2)
(PWM) Pin 8	C5	10	Pin 3 (Analog input 3)
(PWM) Analog Input 7	C6	9	Pin 4 (Analog input 4)
(PWM) Analog Input 6	C7	8	Pin 5 (Analog input 5)
		7	Pin 6 (Analog input 6)
		6	Pin 7 (Analog input 7)
		5	Pin 8 (Analog input 8)
		4	Pin 9 (Analog input 9)
		3	Pin 10 (Analog input 10)
		2	Pin 11 (Analog input 11)
		1	Pin 12 (Analog input 12)

Communication Specification and Pinout

Data Labels

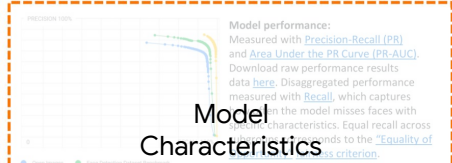
Nutrition Label

Privacy & Security

IoT Security & Privacy Label

Camera Specs	Color camera	Stereo pair	SIMBOL	RATING	MIN	MAX	UNIT
Sensor	IMX224	OV2741	Face	Recognition	4.75	5.25	%
DRIVE / 1500V / 1500V	80° / 80° / 150°	80° / 20° / 150°	Face	Presence	3.5	3.5	%
Resolution	1280x720@30FPS	1280x720@30FPS	Face	Human	1.5	1.5	A
Focus	AF: Auto - DR FT: 30cm -	Fixed Focus 4.5cm -	Face	Object	1.5	1.5	A
Max Frames/s			Face	Temperature	48	58	°C
Framerate	1.5 FPS	1.5 FPS					
Connector	1.27mm	1.27mm					
Electrical Lead Length	3.3mm	3.3mm					
Dimensions	1.9x	1.5x					
Foot size	1.52mm x 1.52mm	1.5x x 1.5mm					

Hardware Characteristics

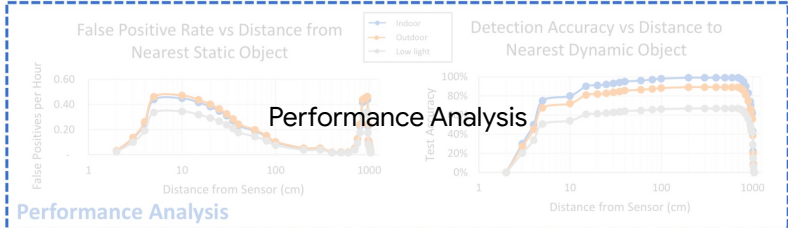


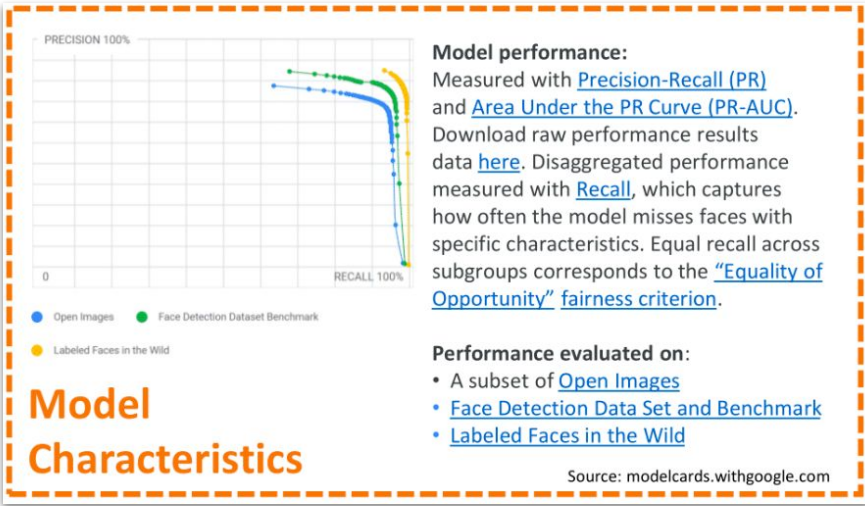
Performance evaluated on:

- A subset of [Open Images](#)
- [Face Detection Data Set and Benchmark](#)
- [Labeled Faces in the Wild](#)

Environmental Impact

390g CO ₂ -eq	23L Water
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Model Characteristics

“Model cards aim to provide a **concise, holistic picture of a machine learning model**. To start, a model card explains **what a model does**, its **intended audience**, and who **maintains it**. A model card also provides insight into the construction of the model, including **its architecture** and the **training data used**.” – Google Cloud

PA1 Person Detection Module

Description: The PA1 Person Detection Module enables you to quickly and easily add smarts to your IoT deployment to monitor and detect for humans. You can use this module indoors and outdoors to understand where and when humans arrive at your deployment site.

Features:

- Real-time detection with Open Images
- Filter a group of people
- Minimum of 100000 (20000 Local)
- Operates in a wide temperature range (0 to 50 °C)
- Features Color and Black-and-White Detection Modules

Use Cases:

- Smart business and home security systems
- Multi-modal key word spotting for virtual assistants
- Occupancy sensors and other infrastructure sensors

Description, Features, and Use Cases

Category	Value
Model Name	PA1 Person Detection Module
Version	1.0.0
Model Type	Person Detection
Model Size	1.5 MB
Model Accuracy	95%
Model Latency	100ms
Model Throughput	1000 FPS
Model Power	1W
Model Temperature	0 to 50 °C
Model Environment	Indoor/Outdoor
Model Hardware	PA1 Person Detection Module
Model Software	PA1 Person Detection Module
Model License	Apache 2.0
Model Contact	Google Cloud
Model Support	Google Cloud
Model Documentation	Google Cloud
Model Training Data	Open Images, Labeled Faces in the Wild
Model Training Method	Deep Learning
Model Training Time	1000000
Model Training Location	Google Cloud
Model Training Hardware	Google Cloud
Model Training Software	Google Cloud
Model Training License	Google Cloud
Model Training Contact	Google Cloud
Model Training Support	Google Cloud
Model Training Documentation	Google Cloud

Communication Spec. & Pinout

Category	Value
Model Name	PA1 Person Detection Module
Version	1.0.0
Model Type	Person Detection
Model Size	1.5 MB
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Data Labels, Privacy & Security, IoT Security & Privacy Label

Compliance

Diagram and Form Factor

Hardware Characteristics

Category	Value
Model Name	PA1 Person Detection Module
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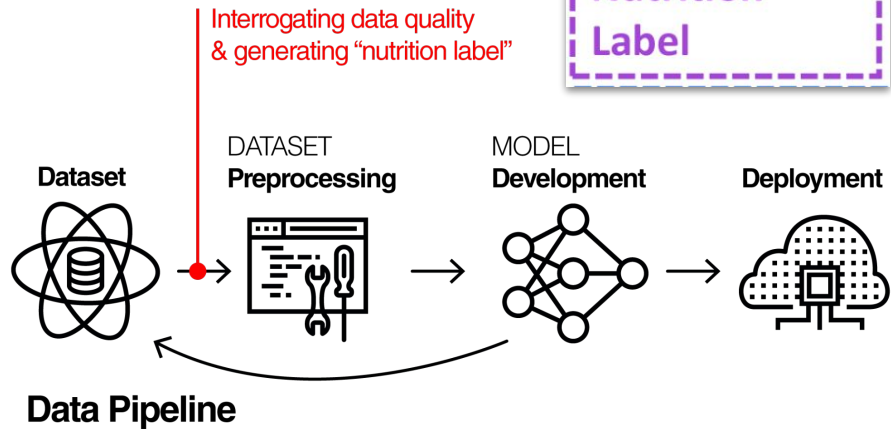
Model performance: Measured with [Precision-Recall \(PR\)](#) and [Area Under the PR Curve \(PR-AUC\)](#). Download raw performance results data [here](#). Disaggregated performance measured with [Recall](#), which captures how often the model misses faces with specific characteristics. Equal recall across subgroups corresponds to the [“Equality of Opportunity” fairness criterion](#).

Performance evaluated on:

- A subset of [Open Images](#)
- [Face Detection Data Set and Benchmark](#)
- [Labeled Faces in the Wild](#)

Source: modelcards.withgoogle.com

Environmental Impact: Env. Impact



Source: datanutrition.org

Dataset Nutrition Label

“There’s a missing step in the AI development pipeline: **assessing datasets** based on **standard quality measures** that are both qualitative and quantitative. We are working on **packaging up these measures** into an easy to use **Dataset Nutrition Label**.” - Dataset Nutrition Project

PA1 Person Detection Module Compliance

Description, Features and Use case

Diagram and Form Factor

Diagrams and Form Factor

Hardware Characteristics

Hardware Characteristics

Communication Spec. & Pinout

Communication Specification and Pinout

Privacy & Security IoT Security & Privacy Label

Dataset Nutrition Label

Model Characteristics

Model performance: Measured with **Precision-Recall (PR)** and **Area Under the PR Curve (PR-AUC)**. Download raw performance results [data here](#). Disaggregated performance measured with **Recall**, which captures how often the model misses faces with specific characteristics. Equal recall across subgroups corresponds to the “**Equality of Opportunity**” fairness criterion.

Performance evaluated on:

- A subset of **Open Images**
- Face Detection Data Set and Benchmark**
- Labeled Faces in the Wild**

Environmental Impact: Env. Impact

Performance Analysis

Performance Analysis

Source: iotsecurityprivacy.org

Sensor data collection	Visual
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

IoT Security & Privacy Label

“... designing a **usable security and privacy label** for smart devices to **help consumers** make informed choices about Internet of Things device purchases and encourage manufacturers to **disclose their privacy and security practices.**” – IoT Security & Privacy

PA1 Person Detection Module

Description, Features and Use case

Description: The PA1 Person Detection Module enables you to quickly and easily add smarts to your IoT deployment to monitor and detect for humans. You can use this module indoors and outdoors to understand where and when humans arrive at your deployment site.

Features:

- Real-time detection with OpenCV
- Filter a group of objects to only those that are a minimum size (minimum 10000 Lux)
- Operates in a wide temperature range (0 to 50 °C)
- Features Color and Black-and-White Detection Modules

Use Cases:

- Smart business and home security systems
- Multi-modal key word spotting for virtual assistants
- Occupancy sensors and other infrastructure sensors

Compliance

Diagram and Form Factor

Source: docs.luxonis.com

Communication Spec. & Pinout

Communication Specification and Pinout

Source: libloading.org, www.luxonis.com, and pinout.xyz

Hardware Characteristics

Category	Value	Unit
Length	40	mm
Width	20	mm
Height	15	mm
Weight	1.5	g
Operating Temperature	0 to 50	°C
Storage Temperature	-20 to 70	°C
Humidity	10 to 90	%
Power Consumption	1.5	W
Power Supply	5V	V
Power Input	5V	V
Power Output	5V	V

Source: docs.luxonis.com

Data Labels

Data Labels

Source: iotsecurityprivacy.org

Model Characteristics

Model performance: Measured with **Precision-Recall (PR)** and **Area Under the PR Curve (PR-AUC)**. Download raw performance results [data here](#). Disaggregated performance measured with **Recall**, which captures how often the model misses faces with specific characteristics. Equal recall across subgroups corresponds to the “**Equality of Opportunity**” fairness criterion.

Performance evaluated on:

- A subset of **Open Images**
- **Face Detection Data Set and Benchmark**
- **Labeled Faces in the Wild**

Source: mediacards.withgoogle.com

Performance Analysis

Performance Analysis

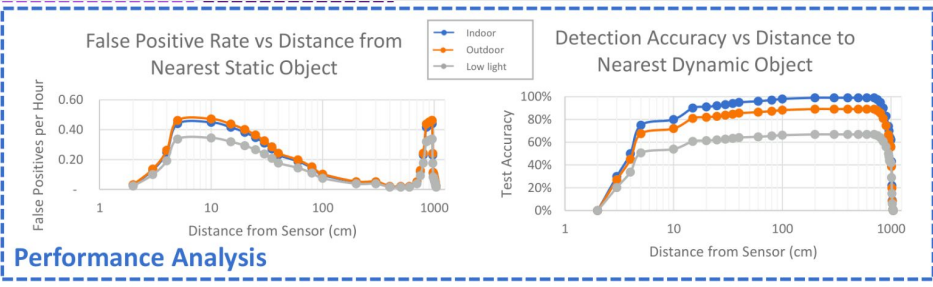
Env. Impact

Environmental Impact

330g CO₂e/g

2.5g Water/g

We require **systematic methodologies** to evaluate how an **end-to-end system** performs under **real-world conditions**



PA1 Person Detection Module

Description, Features and Use case

Description: The PA1 Person Detection Module enables you to quickly and easily add smarts to your IoT deployment to monitor and detect for humans. You can use this module indoors and outdoors to understand where and when humans arrive at your deployment site.

Features:

- Real-time detection with OpenCV
- Inbuilt person detection
- Filter a person's minimum or maximum distance (0 to 20000 cm)
- Operates in a wide temperature range (0 to 50 °C)
- Features Color and Black-and-White Detection Modules

Use Cases:

- Smart business and home security systems
- Multi-modal key word spotting for virtual assistants
- Occupancy sensors and other infrastructure sensors

Diagrams and Form Factor

Compliance

Diagram and Form Factor

Diagrams and Form Factor

Hardware Characteristics

Category	Value
Model	PA1-001
Manufacturer	PA1-001
Part Number	PA1-001
Version	1.0
Release Date	2023-01-01
Weight	100g
Dimensions	100x50x20mm
Power Consumption	1W
Operating Temperature	0 to 50 °C
Storage Temperature	-20 to 70 °C
Humidity	10 to 90% RH
Material	PCB
RoHS	Compliant
REACH	Compliant

Communication Spec. & Pinout

Communication Specification and Pinout

Data Labels

Privacy & Security

IoT Security & Privacy Label

Model Characteristics

Model performance: Measured with **Precision-Recall (PR)** and **Area Under the PR Curve (PR-AUC)**. Download raw performance results data [here](#). Disaggregated performance measured with **Recall**, which captures how often the model misses faces with specific characteristics. Equal recall across subgroups corresponds to the "Equality of Opportunity" fairness criterion.

Performance evaluated on:

- A subset of **Open Images**
- **Face Detection Data Set and Benchmark**
- **Labeled Faces in the Wild**

Environmental Impact

Env. Impact

330g CO₂e/kg

23% Water

Performance Analysis



ML sensors ought to be **tested by 3rd party certification agencies or bodies that specialize in AI/ML technologies.**

PA1 Person Detection Module

Description, Features and Use case

Description, Features, and Use Cases

Communication Spec. & Pinout

Communication Specification and Pinout

Diagram and Form Factor

Hardware Characteristics

Hardware Characteristics

Data Labels

Data Nutrition Label

Privacy & Security

IoT Security & Privacy Label

Model Characteristics

Model Characteristics

Env. Impact

Environmental Impact

Performance Analysis

Performance Analysis

32

IoT ≈ The Internet of Trash?

Environmental Impact: Full report can be found [here](#).

Environmental Impact

390g CO₂-eq

23L Water

Source: st.com

We must quantify the effects of ML sensors in terms of carbon emissions. Carbon emissions have two sources: (1) **operational energy consumption**, and (2) **hardware manufacturing and infrastructure**. The former has been decreasing thanks to software and hardware innovations but the **total footprint is growing**.

PA1 Person Detection Module

Description, Features and Use case

Compliance

Diagram and Form Factor

Diagrams and Form Factor

Hardware Characteristics

Hardware Characteristics

Communication Spec. & Pinout

Communication Specification and Pinout

Data Labels

Privacy & Security

IoT Security & Privacy Label

Model Characteristics

Environmental Impact: Full report can be found [here](#).

Environmental Impact

390g CO₂-eq

23L Water

Source: st.com

Performance Analysis

Performance Analysis

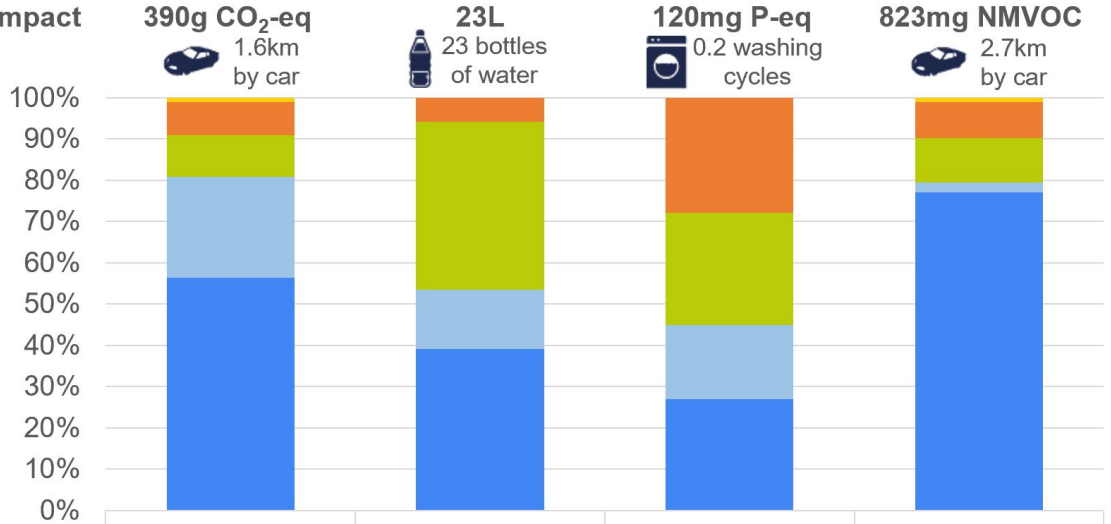
False Positive Rate vs Distance from Nearest Static Object

Detection Accuracy vs Distance to Nearest Dynamic Object

Assessing the Environmental Impact of an MCU



Total Impact



	Climate Change	Water Demand	Freshwater Eutrophication	Protochemical Oxidant Formation
End of Life	<1%	<1%	<1%	<1%
Logistics	1%	<1%	<1%	1%
Use	8%	6%	28%	8%
Raw Materials	10%	41%	27%	10%
Production: Other	24%	15%	18%	2%
Production: Energy Consumption	56%	39%	27%	71%

Source:

https://www.st.com/content/st_com/en/about/st_approach_to_sustainability/sustainability-priorities/sustainable-technology/eco-design/footprint-of-a-microcontroller.html

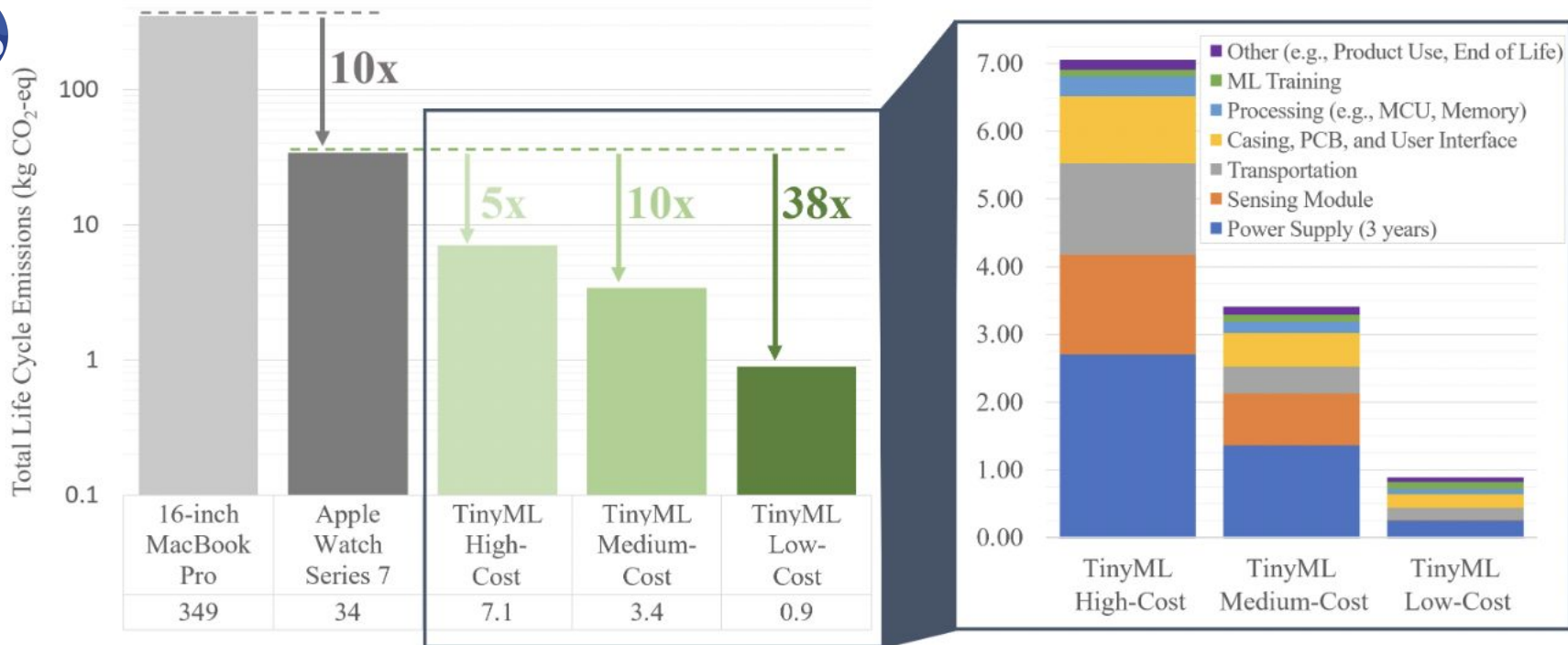


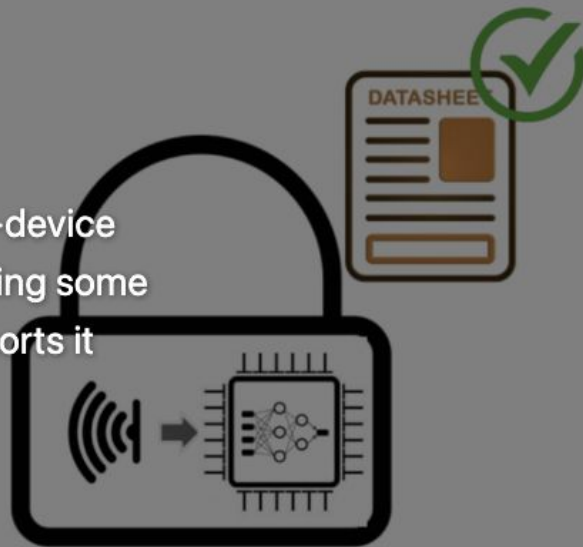
Figure 4. A breakdown of different TinyML system footprints highlights that the footprint is largely attributable to the embodied footprint of the power supply, onboard sensors, and transportation. Note that actuator and connectivity blocks from Pirson and Bol [21] are encapsulated in “Other” and “Processing”, respectively, while “Product Use” captures the operational footprint. The carbon footprint of TinyML Systems was also compared with Apple’s Series 7 Watch [12] and 16-inch MacBook Pro [11] as baseline references. For more details and to compute the footprint of your own TinyML system see github.com/harvard-edge/TinyML-Footprint.

ML Sensors - Guiding Set of Principles

1. We need to **raise the level of abstraction** to enable ease of use for scalable deployment of ML sensors; not everyone should be required to be a developer or an engineer to leverage ML sensors into their ecosystem.
2. The ML sensor's **design should be inherently data-centric** and defined by its input-output behavior instead of exposing the underlying hardware and software mechanisms that support ML model execution.
3. An ML sensor's **implementation must be clean and complexity-free**. Features such as reusability, software updates, and networking must be thought through to ensure data privacy and secure execution.
4. ML sensors **must be transparent, indicating in a publicly and freely accessible ML sensor datasheet** all the relevant information to supplement the traditional information available for hardware sensors.
5. We as a community should aim to **foster an open ML sensors ecosystem by maximizing data, model, and hardware transparency** where possible, without necessarily relinquishing any claim to intellectual property.

Machine Learning Sensors

An ML sensor is a self-contained system that utilizes on-device machine learning to extract useful information by observing some complex set of phenomena in the physical world and reports it through a simple interface to a wider system.



Machine learning sensors represent a paradigm shift for the future of embedded machine learning applications. Current instantiations of embedded ML suffer from complex integration, lack of modularity, and privacy and security concerns from data

Machine Learning Sensors - M x +

misenors.org

TinyML Harvard MLC Research Seed CS141 TimeBuddy VJs Funding Enterprise - Suppl... Geo Chart Examp... Other Bookmarks

MLSensors
Machine Learning Sensors

Home Whitepaper GitHub Email Team

Machine Learning Sensors

An ML sensor is a self-contained system that utilizes on-device machine learning to extract useful information by observing some complex set of phenomena in the physical world and reports it through a simple interface to a wider system.

Machine learning sensors represent a paradigm shift for the future of embedded machine learning applications. Current instantiations of embedded ML suffer from complex integration, lack of modularity, and privacy and security concerns from data movement. ML sensors provide a more data-centric paradigm for embedding sensor intelligence on edge devices to combat these challenges.

Our vision for "sensor 2.0" entails segregating sensor input data and ML processing from the wider system at the hardware level and providing a thin interface that mimics traditional sensors in functionality. This separation leads to a modular and easy-to-use ML sensor device. ML sensors increase privacy and accuracy while making it easier for system builders to integrate ML into their products as a simple component.

To learn more about our approach, check out our [whitepaper on arXiv](#).

Challenges

Interface

Standards

Ethics

Machine Learning Sensors - M x +

misenors.org

TinyML Harvard MLC Research Seed CS141 TimeBuddy VJs Funding Enterprise - Suppl... Geo Chart Examp... Other Bookmarks

Challenges

Interface

What universal interface is needed for ML Sensors?

Standards

What standards need to be in place for ML Sensors?

Ethics

What ethical considerations are needed for ML Sensors?

Call for Working Group Members

We are actively growing our working group. If you would like to be a part of it please email us at: ml-sensors@googlegroups.com!

Example ML Sensor Datasheet

This illustrative example datasheet highlighting the various sections of an ML Sensor datasheet. On the top, we have the items currently found in standard datasheets: the description, features, use cases, diagrams and form factor, hardware characteristics, and communication specification and pinout. On the bottom, we have the new items that need to be included in an ML sensor datasheet: the ML model characteristics, dataset nutrition label, environmental impact analysis, and end-to-end performance analysis. While we compressed this datasheet into a one-page illustrative example by combining features and data from a mixture of sources, on a real datasheet, we assume each of these sections would be longer and include additional explanatory text to increase the transparency of the device to end-users. Interested users can find the most up-to-date version of the datasheet online at <https://github.com/harvard-edge/ML-Sensors>.

PA1 Person Detection Module

Description: The PA1 Person Detection Module enables you to quickly and easily add smarts to your IoT deployment to monitor and detect for humans. You can use this module indoors and outdoors to understand where and when humans arrive at your deployment site.

Features:

- Real-time Person Detection with On-Device ML

Compliance

Recap of ML Sensors

1. We need to **raise the level of abstraction** to enable ease of use for scalable deployment of ML sensors; not everyone should be required to be a developer or an engineer to leverage ML sensors into their ecosystem.
2. The ML sensor's **design should be inherently data-centric** and defined by its input-output behavior instead of exposing the underlying hardware and software mechanisms that support ML model execution.
3. An ML sensor's **implementation must be clean and complexity-free**. Features such as reusability, software updates, and networking must be thought through to ensure data privacy and secure execution.
4. ML sensors **must be transparent, indicating in a publicly and freely accessible ML sensor datasheet** all the relevant information to supplement the traditional information available for hardware sensors.
5. We as a community should aim to **foster an open ML sensors ecosystem by maximizing data, model, and hardware transparency** where possible, without necessarily relinquishing any claim to intellectual property.

Call to Action

Radcliffe exploratory seminar to determine:



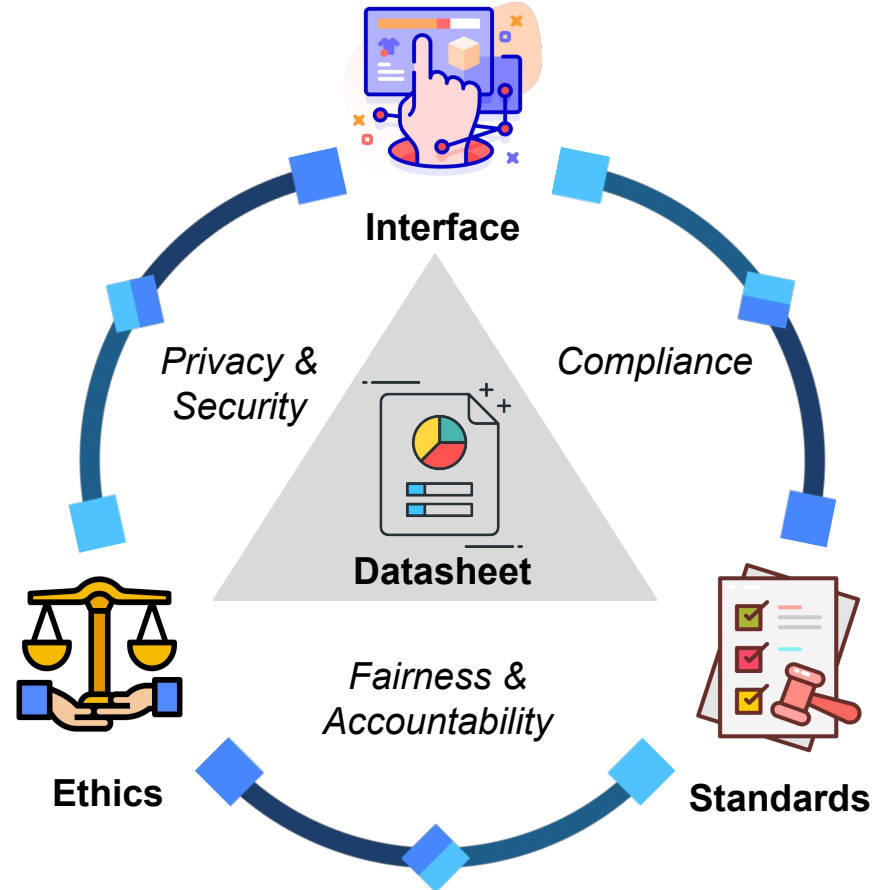
What ethical considerations are necessary when developing ML sensors?



What compliance standards must be met by ML sensor developer and manufacturers?



How should ML sensors interface with existing systems?



mlsensors.org

<https://github.com/harvard-edge/ML-Sensors>

arXiv:2206.03266v1 [cs.LG] 7 Jun 2022

MACHINE LEARNING SENSORS

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Zain Asgar¹ Sachin Katti¹ Vijay Janapa Reddi²

¹Stanford University ²Harvard University

ABSTRACT

Machine learning sensors represent a paradigm shift for the future of embedded machine learning applications. Current instantiations of embedded machine learning (ML) suffer from complex integration, lack of modularity, and privacy and security concerns from data movement. This article proposes a more data-centric paradigm for embedding sensor intelligence on edge devices to combat these challenges. Our vision for “sensor 2.0” entails segregating sensor input data and ML processing from the wider system at the hardware level and providing a thin interface that mimics traditional sensors in functionality. This separation leads to a modular and easy-to-use ML sensor device. We discuss challenges presented by the standard approach of building ML processing into the software stack of the controlling microprocessor on an embedded system and how the modularity of ML sensors alleviates these problems. ML sensors increase privacy and accuracy while making it easier for system builders to integrate ML into their products as a simple component. We provide examples of prospective ML sensors and an illustrative datasheet as a demonstration and hope that this will build a dialogue to progress us towards sensor 2.0.

1 INTRODUCTION

Since the advent of AlexNet [43], deep neural networks have proven to be robust solutions to many challenges that involve making sense of data from the physical world. Machine learning (ML) models can now run on low-cost, low-power hardware capable of deployment as part of an embedded device. Processing data close to the sensor on an embedded device allows for an expansive new variety of always-on ML use-cases that preserve bandwidth, latency, and energy while improving responsiveness and maintaining data privacy. This emerging field, commonly referred to as embedded ML or tiny machine learning (TinyML) [73, 18, 39, 59], is paving the way for a prosperous new array of use-cases, from personalized health initiatives to improving manufacturing productivity and everything in-between.

However, the current practice for combining inference and sensing is cumbersome and raises the barrier of entry to embedded ML. At present, the general design practice is to design or leverage a board with decoupled sensors and compute (in the form of a microcontroller or DSP), and for the developer to figure out how to run ML on these embedded platforms. The developer is expected to train and optimize ML models and fit them within the resource constraints of the embedded device. Once an acceptable prototype implementation is developed, the model is integrated with the rest of the software on the device. Finally, the widget is tethered to the device under test to run inference. The current approach is slow, manual, energy-inefficient, and error-prone.

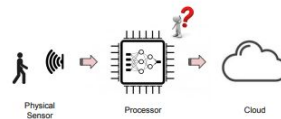


Figure 1. The Sensor 1.0 paradigm tightly couples the ML model with the application processor and logic, making it difficult to provide hard guarantees about the ML sensor’s ultimate behavior.

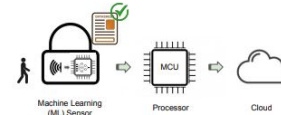


Figure 2. Our proposed Sensor 2.0 paradigm. The ML model is tightly coupled with the physical sensor, separate from the application processor, and comes with an ML sensor datasheet that makes its behavior transparent to the system integrators and developers.

It requires a sophisticated understanding of ML and the intricacies of ML model implementations to optimize and fit a model within the constraints of the embedded device.