

Applied Al Track Wrap-up

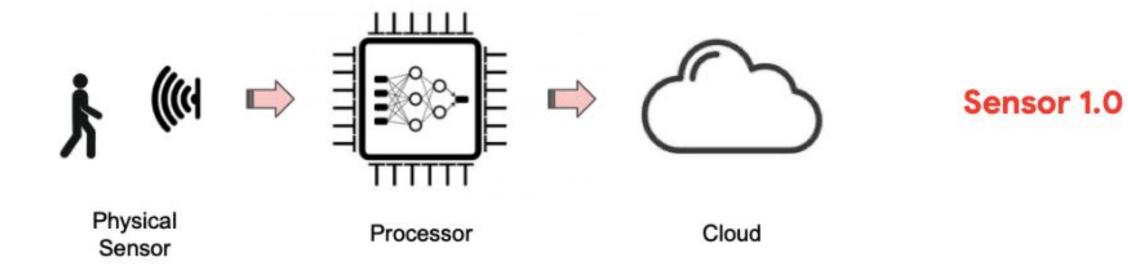
Prof. Marcelo J. Rovai rovai@unifei.edu.br

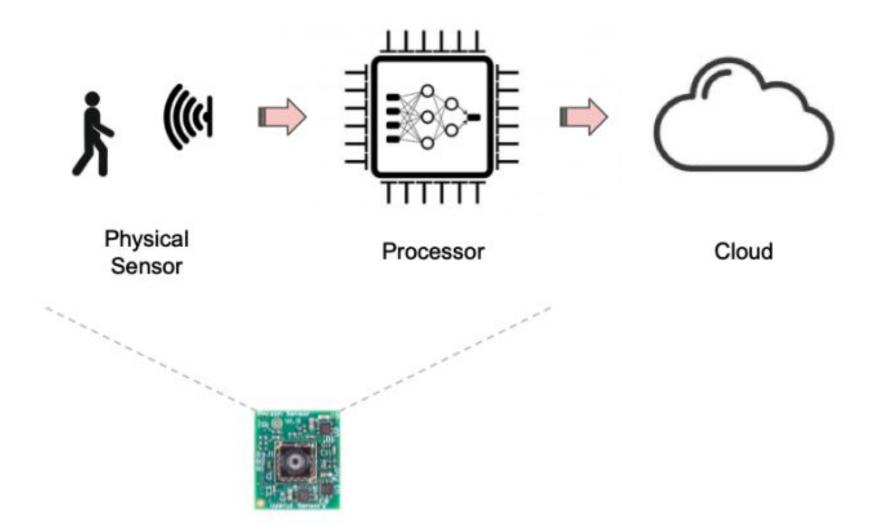
UNIFEI - Federal University of Itajuba, Brazil TinyML4D Academic Network Co-Chair

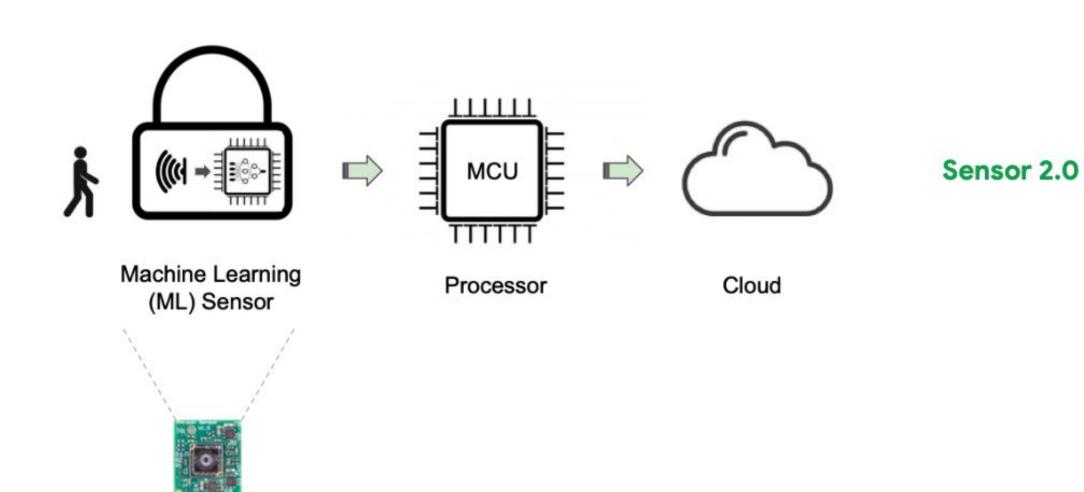




The Future of the EdgeAl



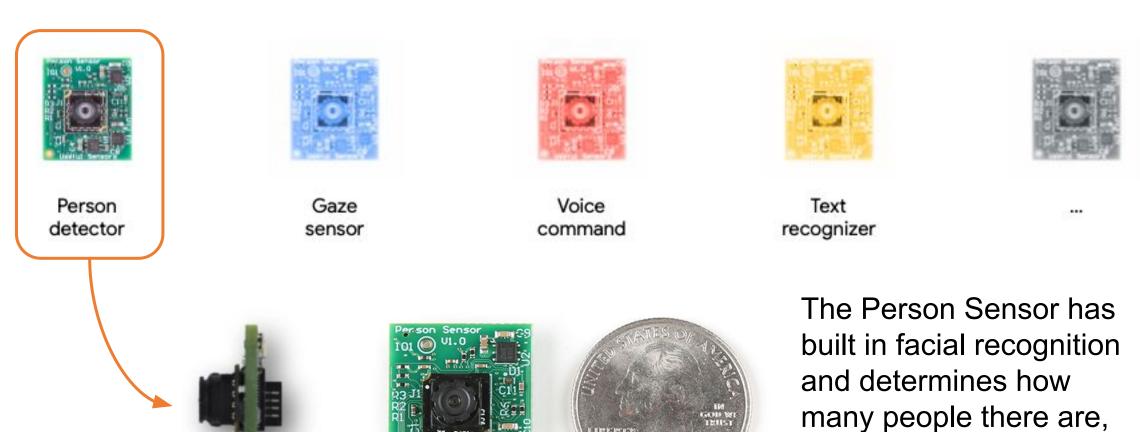






as well as their relative

position.



LIBERTY

USD 10 -> https://www.sparkfun.com/products/21231

Bosch BME688 - Environmental sensing with Al









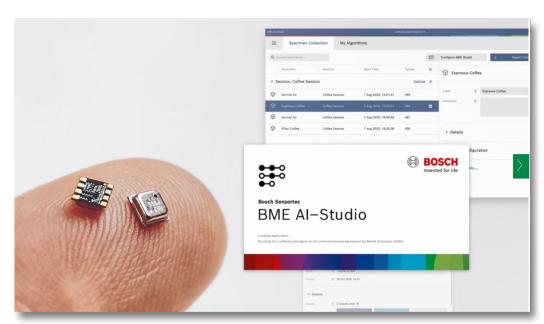
Relative humidity barometric pressure

Excellent temperature stability

Humidity

Gas sensing





https://www.bosch-sensortec.com/products/environmental-sensors/gas-sensors/bme688/

mlsensors.org https://qithub.com/harvard-edge/ML-Sensors

MACHINE LEARNING SENSORS

Pete Warden ¹ Matthew Stewart ² Brian Plancher ² Colby Banbury ² Shvetank Prakash ² Emma Chen ² Zain Asgar ¹ Sachin Katti ¹ Vijay Janapa Reddi ²

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

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Jun

[cs.LG]

arXiv:2206.03266v1

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.

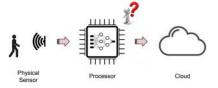


Figure 1. The Sensor 1.0 paradigm tightly couples the ML model with the application processor and logic, making it difficult to provide hard guarantees about the ML sensor's ultimate behavior.

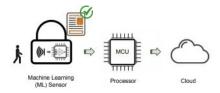
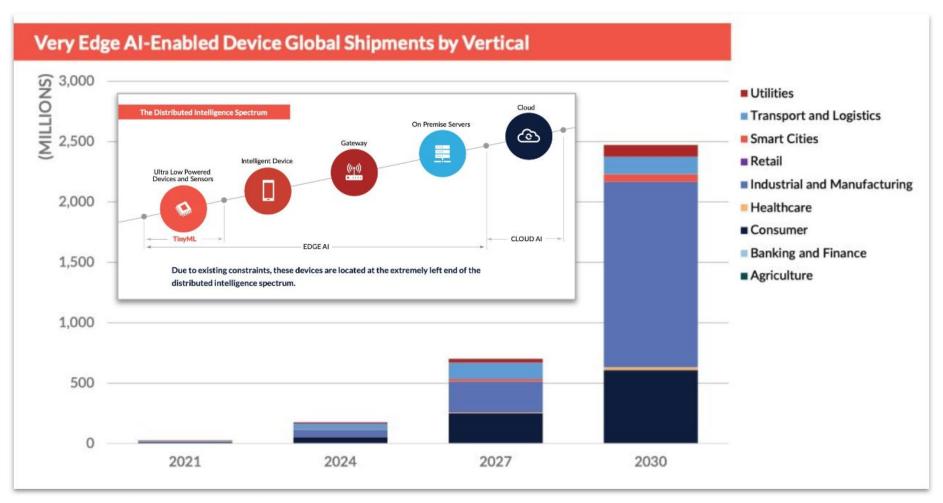


Figure 2. Our proposed Sensor 2.0 paradigm. The ML model is tightly coupled with the physical sensor, separate from the application processor, and comes with an ML sensor datasheet that makes its behavior transparent to the system integrators and developers.

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.

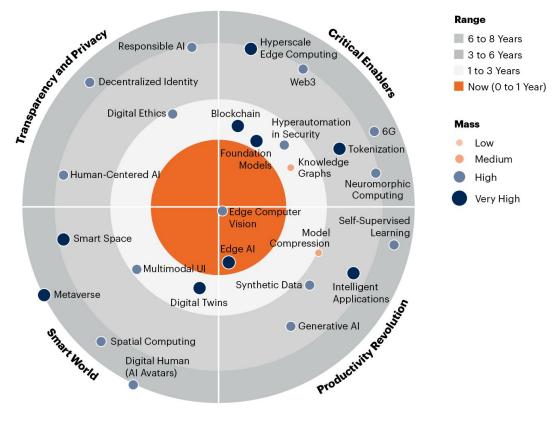
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Massive Potential for Impact



Source: ABI Research: TinyML

2023 Gartner Emerging Technologies and Trends Impact Radar



gartner.com

Note: Range measures number of years it will take the technology/trend to cross over from early adopter to early majority adoption. Mass indicates how substantial the impact of the technology or trend will be on existing products and markets.

Source: Gartn

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Gartner

Edge AI has a very high impact potential, and it is for now!

Conclusion



The Future of ML is Tiny and Bright

Vijay Janapa Reddi, Ph. D. | Associate Professor | John A. Paulson School of Engineering and Applied Sciences | Harvard University |



Responsible Al

Suzan Kennedy, Ph.D.



SciTinyML Seminar - Slides

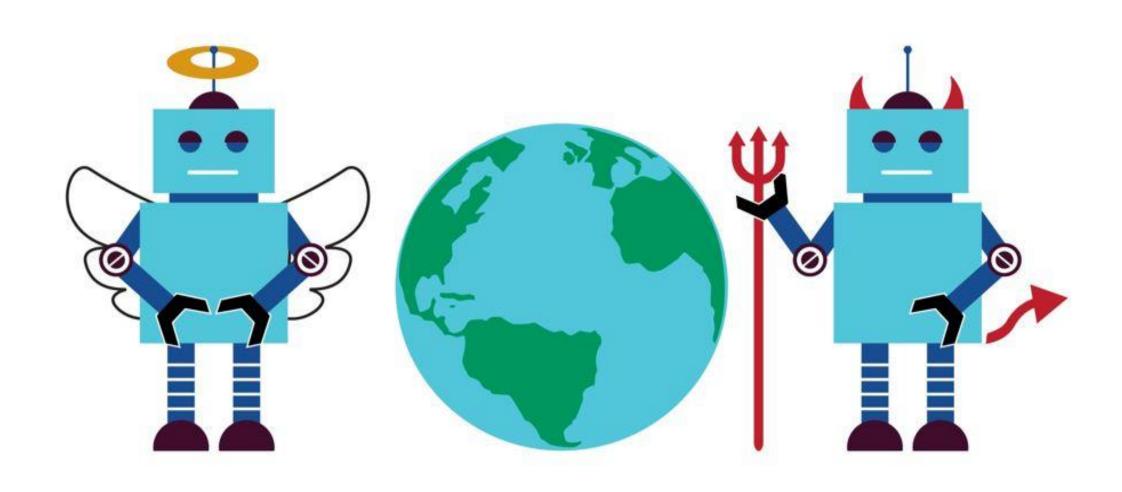


SciTinyML Seminar - Video





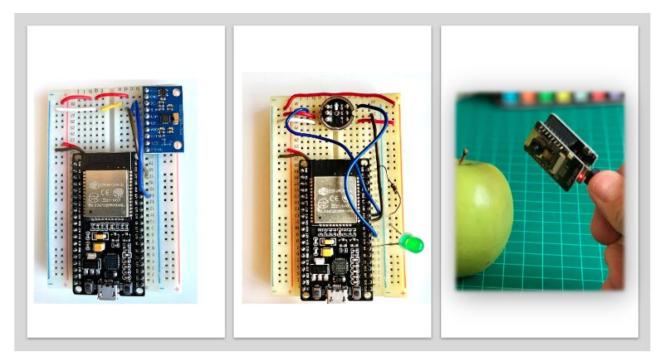
Responsible Al



To learn more ...

ESP32-TinyML

Exploring TinyML with ESP32 MCUs.





Seeed-XIAO-BLE-Sense

KWS, Anomaly Detection & Motion Classification and Micropython - Exploring the Seeed XIAO BLE Sense.









TinyML Made Easy: So Classification (KWS)



XIAO-ESP32S3-Sense







Exploring Machine Learning with the new XIAO ESP32S3 MJRoBot (Marcelo Roval)



TinyML Made Easy: Image Classification MJRoBot (Marcelo Rovai)



To learn more ...

- IESTI01 TinyML Machine Learning for Embedding Devices (Videos: Pt)
- WALC 22 Applied AI TinyML (Videos in Spanish)
- Professional Certificate in Tiny Machine Learning (TinyML) edX/Harvard
- Introduction to Embedded Machine Learning Coursera/Edge Impulse
- Computer Vision with Embedded Machine Learning Coursera/Edge Impulse
- "Deep Learning with Python" book by François Chollet
- "TinyML" book by Pete Warden, Daniel Situnayake
- "TinyML Cookbook" by Gian Marco Iodice
- "Al at the Edge" book by Daniel Situnayake, Jenny Plunkett
- "MACHINE LEARNING SYSTEMS for TinyML" Collaborative effort
- Edge Impulse Expert Network

TinyML4D Show&Tell Presentations

Date	Thread	Video
August 31 st , 2023 May 25th, 2023	TBD <u>Thread here</u>	Video here when ready Video here when ready
April 20 th , 2023	<u>Thread here</u>	https://youtu.be/uoM_ljXjDFY
March 30th, 2023	thread here	https://youtu.be/UQ0I-SwBwUY
February 23rd, 2023	thread here	https://youtu.be/BAEdil7X68Y
January 26th, 2023	thread here 17	https://youtu.be/-0xRZ-5UYUc 9
December 1st, 2022	thread here 2	https://youtu.be/e49pkjnIMIQ 8
October 27th, 2022	thread here 2	https://youtu.be/s8_hKpOWUwY 1

<u>TinymML4D Academic Network Show and Tell Main Index.</u>

The TinyML4D Academic Network Students should use this form to sign up for the latest presentations. https://forms.gle/ic52HZMqVv4pBrkP7.2

The Show and Tell are typically held at 2 pm UTC on the last Thursday of each month and will take place in this Zoom room.

https://zoom.us/j/95229860797 1

Meeting ID: 952 2986 0797 Passcode: 141278

Projects by Students (UNIFEI – IESTI01)

Sound:

- Earthquake detection
- Covid Detection (cough)
- Key Detection
- Pulmonary Disease
- Snore Detection
- Bionic Hand Control

Other Sensors:

- Bionic Hand Finger Detection
- Electric Charges
- ECG Fibrial Atrilation detection

• Image:

- Mask Detection
- Forest Fire Detection
- Helmet Detection
- Water Consumption (hydrometer)
- Sign Language
- Coffee Disease Classification
- Bee Counting

Vibration:

- Personal Trainer
- Bearing Anomaly Detection

Thanks



