

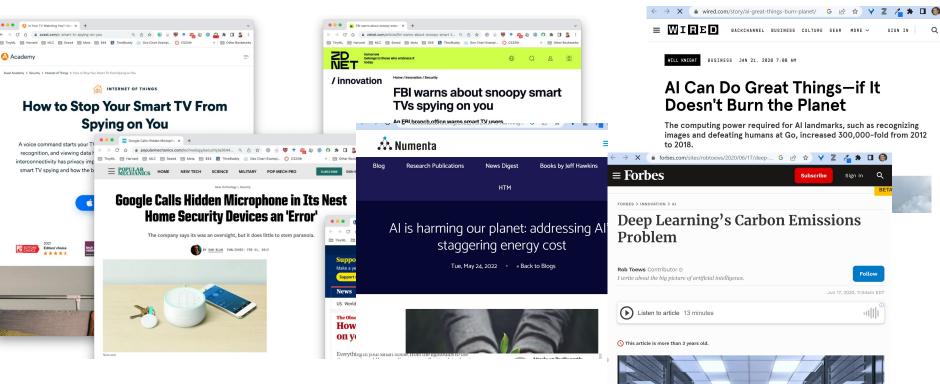
Responsible TinyML



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brianplancher.com



How can TinyML support Responsible AI?



How can TinyML support Responsible AI?



Accessibility / Education

Promoting Accessibility / Education

Full Courses Language of Language of Organization Course Name Date of Course Target Audience Links Instruction Materials Course 1-3 Website Course 4 Website edX tinyML Specialization Launched Everyone English English All Materials by Harvard University 2020-2022 All Colabs Arduino Library Embedded Machine Learning on Course 1 Launcher **=**0 Coursera English English Course 2 Everyone 2021-2022 by Edge Impulse All Materials ESE3600: Tiny Machine Learning Undergraduate and English English Website and Materials by the University of Pennsylvania Graduate Students MIT 6.S965 Website TinyML and Efficient Deep Fall 2022 English Graduate Students English Materials Learning 2022.1 Website and Materials UNIFELIESTI01 Jan 2021 2021.2 Website and TinvML - Machine Learning for Undergraduate Students Portuguese English Materials **Embedding Devices** 2021.1 Website and Materials 2022 Website and Harvard CS249r Sept 2020 -Assignments Graduate Students English English Tiny Machine Learning 2020 Website 2020 Assignments

Workshops

Lead Organizers	Workshop Name	Date of Workshop	Target Audience	Language of Instruction	Language of Materials	Links
(B)	Morocco Al Summer School 2023	July 2023	Everyone	English	English	Website TinyML Part 1 TinyML Part 2
CTP B B	EdgeMLUP 2023 Workshop on Widening Access to TinyML Network by Establishing Best Practices in Education	July 2023	Everyone	English	English	Website and Materials
⊕ ♥ ® ■	SciTinyML 2023 Scientific Use of Machine Learning on Low- Power Devices	April 2023	Everyone	English	English	Website and Materials
@ (9	TinyML at AAU A Workshop at Addis Ababa University	March 2023	Everyone	English	English	Materials
<u>(A)</u>	Artificial Intelligence and its Integration with Everyday Life An Introduction to TinvML by Edwin Marte at	November 2022	Everyone	Spanish	Spanish	Materials

TinyMLedu.org





Foundations of TinyML

Focusing on the basics of machine learning and embedded systems, such as smartphones. this course will introduce you to the "language" of TinyML.

Take the Course on edi



Applications Of TinyML

Get the opportunity to see TinyML in practice You will see examples of TinvML applications for Tiny applications such as keyword spotting, visual wake words, and gesture recognition.



Deploying TinyML

Learn to program in TensorFlow Lite for microcontrollers so that you can write the code, and deploy your model to your very own Tiny microcontroller. Before you know it, you'll maintain (tiny) Machine Learning models in be implementing an entire TinyML application. production at scale.



MLOps for Scaling TinvML

This course introduces learners to Machine Learning Operations (MLOps) through the lens of TinyML (Tiny Machine Learning). Learners explore best practices to deploy, monitor, and



Computer Vision with **Embedded Machine** Learning

This course, offered by a partnership amono Edge Impulse, OpenMV, Seeed Studio, and the TinyML Foundation, will give you an understanding of how deep learning with neural networks can be used to classify images and detect objects in images and videos

Impulse Platform

Introduction to

Learning

Embedded Machine

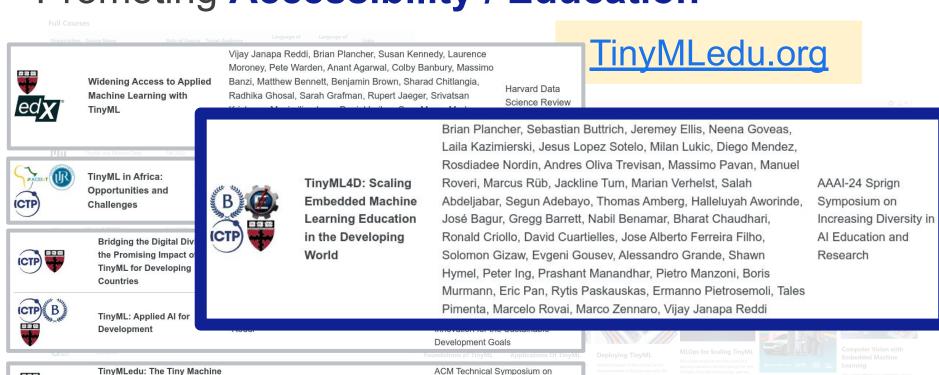
This course will give you a broad overview of how machine learning works, how to train networks to microcontrollers using the Edge

Promoting Accessibility / Education

Learning Open Education

Initiative

Brian Plancher, Vijay Janapa Reddi



Computer Science Education

(SIGCSE)

Global Embedded ML Education Opportunities:

Low Resource
Requirements

Interdisciplinary Focus

Low Cost

Low Connectivity

Embedded Devices (loT)

Global Embedded ML Education Opportunities:

Low Resource Requirements

Interdisciplinary Focus and **Applied** Learning

(IoT)

Low Power TinyML ML / DL **Low Cost Low Connectivity**



Challenges Challenges Global Embedded ML Education Opportunities:

Software and Hardware Fragmentation









Challenges Global Embedded ML Education Opportunities:

Software and Hardware Fragmentation

Affordability Barriers and Localization Roadblocks



Language and Local Relevance



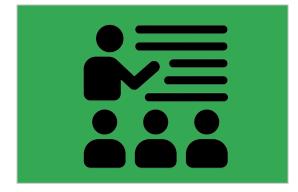
Challenges Global Embedded ML Education Opportunities:

Software and Hardware Fragmentation

Affordability Barriers and Localization Roadblocks

Educator Readiness and Research Incentives







3 - 7 July 2023 An ICTP Meeting Trieste, Italy

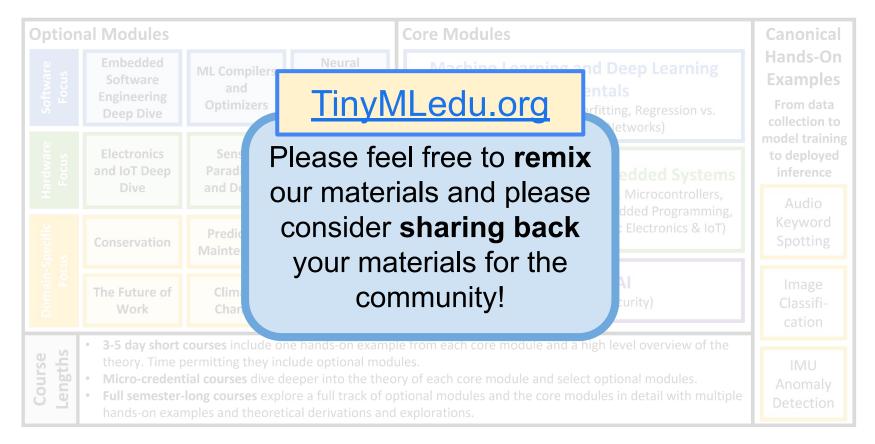




Towards a Modular Curriculum

Optional Modules Core Modules				Canonical		
Software Focus	Embedded Software Engineering Deep Dive	ML Compilers and Optimizers	Neural Network Architecture and Design	Machine Learning and Deep Learning Fundamentals (E.g., Models, Training, Overfitting, Regression vs. Classification, Neural Networks)		Hands-On Examples From data collection to
Hardware Focus	Electronics and IoT Deep Dive	Sensor Paradigms and Design	Device Design and Deployment	Data Centric Al (E.g., Data Collection, Pre- Embedded Systems (E.g, Microcontrollers, Embedded Programming,		model training to deployed inference Audio
ain-Specific Focus	Conservation	Predictive Maintenance	Smart Cities	and Post-Processing)	Keyword Spotting	
Domain- Foc	The Future of Work	Climate Change	Healthcare	Respor (E.g., Bias, Pr	Image Classifi- cation	
 3-5 day short courses include one hands-on example from each core module and a high level overview of the theory. Time permitting they include optional modules. Micro-credential courses dive deeper into the theory of each core module and select optional modules. Full semester-long courses explore a full track of optional modules and the core modules in detail with multiple hands-on examples and theoretical derivations and explorations. 						IMU Anomaly Detection

Towards a Modular Curriculum



Calls to Action

Assessing Our Educational Programs

Improving Accessibility of Hardware

- Maintaining Open-Source Software and Courseware
- Growing a Research
 Community

Embedded ML Model and Data Zoo

Increased Outreach and Diversity Efforts

Calls to Action

Assessing Our Educational Programs

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Underrepresentation of All rights reserved. CC BY-NC-SA 4.0 Women in Robotics Research

Calls to Action

ieeexplore.ieee.org/document/10474552

TABLE 1. FAR for CS and engineering subfields based on prior work and including our result for robotics [1], [3], [4] (data from 2017 to 2023).

FIELD	FAR (%)
CS education	42
Human-computer interaction	26
CS overall average	16–26
Knowledge systems	19
Software engineering and languages	14
Artificial intelligence	12
Robotics	11–12 (our analysis)
Computer systems	10
Theory and algorithms	8

As has been noted in related works, this kind of methodology has many flaws and does not take into account much of the nuance in gender, including issues of bias, misperception, and nonbinary identities [7], [8]. However, we hope that this initial study will help add to the robotics community's understanding of the current state of gender diversity and, at a minimum, provide directionally correct data to help with future diversity, equity, and inclusion efforts.

Sustainability / Conservation

Promoting Sustainability / Conservation

TinyMLedu.org



How TinyML Can be Leveraged to Solve Environmental Problems: A Survey

Hatim Bamoumen, Anas Temouden, Nabil Benamar, Yousra Chtouki

Innovation and Intelligence for Informatics, Computing, and Technologies







Is TinyML Sustainable?

Assessing the Environmental Impacts of Machine Learning on Microcontrollers Shvetank Prakash, Matthew Stewart, Colby Banbury, Mark Mazumder, Pete Warden, Brian Plancher, Vijay Janapa Reddi Communications of the ACM (CACM)



Smart Buildings: Water Leakage Detection Using TinvML

Othmane Atanane, Asmaa Mourhir, Nabil Benamar, Marco Zennaro

Sensors

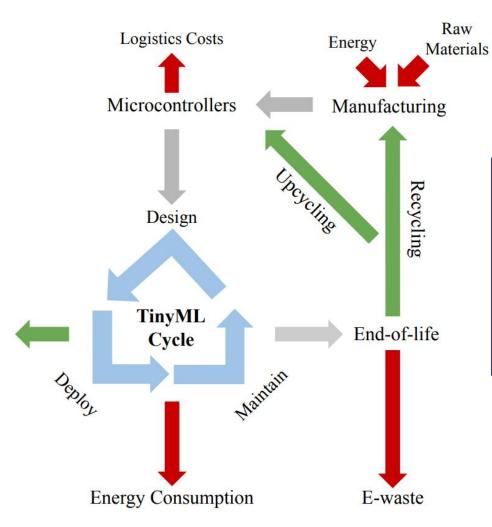


Classifying Mosquito Wingbeat Sound Using TinyML

Moez Altayeb, Marco Zennaro, Marcelo Rovai

ACM Conference on Information Technology for Social Good





TinyML can support the SDGs but comes with costs. What is the net impact?

Building Representative Systems

Cost Level	High Cost	Medium Cost	Low Cost	
Application	Image C	Image Classification		
Size	Large	Compact	Compact	







harvard-edge.github.io/TinyML-Footprint/

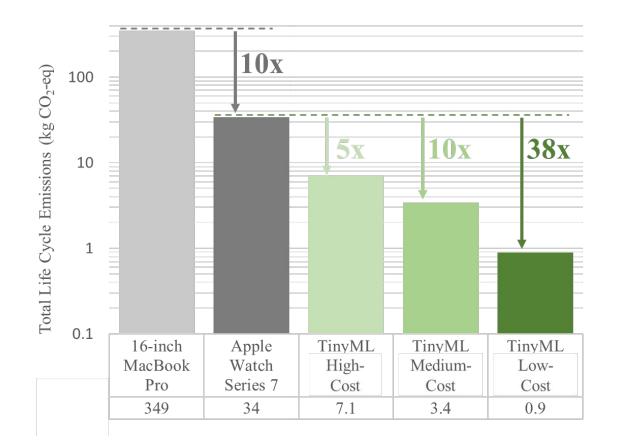
Embodied and Operational CO2 Footprint ML Training Casing Power Supply 100 Sensing Others Transport Indicator LED UI (g CO2e (log scale) Use-Stage reference For more information on the usage of this TinyML CO2 Footprint Calculator, please see our paper and documentation at github.com/harvard-edge/TinyML-Footprint

TinyML CO₂ Footprint Calculator





TinyML Systems in Context



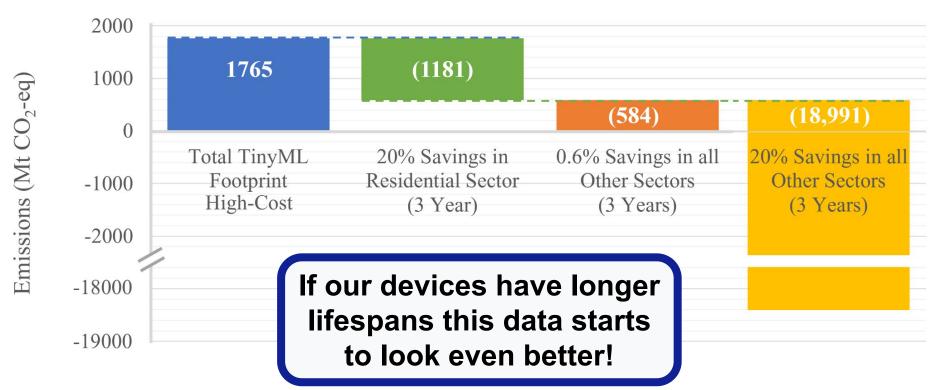
5x to 38x
Savings
over a
3-year
lifespan!

What if we scale to 250bn devices?

There are around **250bn MCUs** deployed today and around **15bn IoT** devices

IoT Device Growth						
	~15 Billion	>50 Billion	>100 billion	>250 Billion	>1 Trillion	
Linear	2023	2041	2067	2144	2531	
Exponential	2023	2032	2036	2043	2053	

What if we scale to 250bn devices?



Privacy / Security

TinyML will soon be everywhere!

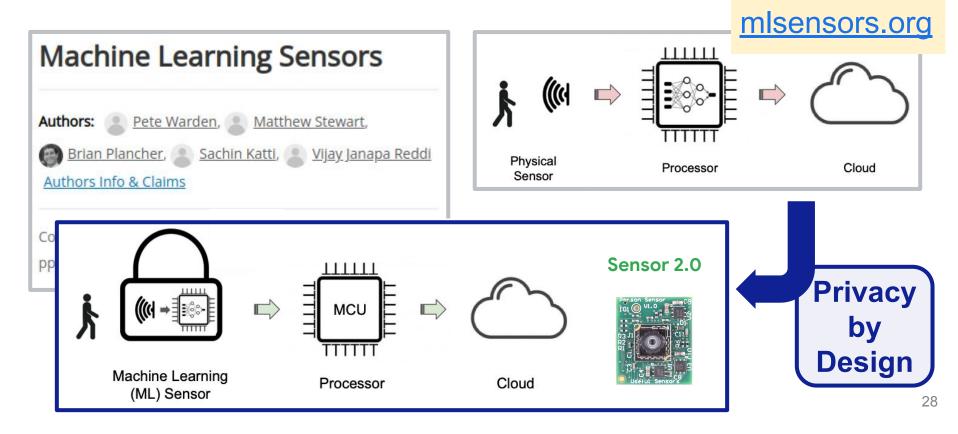
loT 1.0: Internet of Things



loT 2.0: Intelligence on Things



What is a Machine Learning Sensor?



We suggest transparency as a core value

Datasheets for Machine Learning Sensors:

Towards Transparency, Auditability, and Responsibility for Intelligent Sensing

MATTHEW STEWART, Harvard University,

PETE WARDEN, Stanford University, Useful Sensors,

YASMINE OMRI, Harvard University,

SHVETANK PRAKASH, Harvard University,

JOAO SANTOS, Harvard University,

SHAWN HYMEL, Edge Impulse,

BENJAMIN BROWN, Harvard University,

JIM MACARTHUR, Harvard University,

NAT JEFFRIES, Useful Sensors,

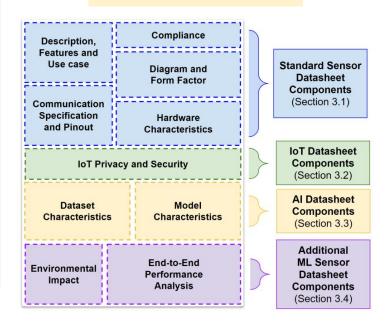
SACHIN KATTI, Stanford University,

BRIAN PLANCHER, Barnard College, Columbia University,

VIJAY JANAPA REDDI, Harvard University,

arxiv.org/abs/2306.08848

mlsensors.org



Materiality and Risk in the Age of Pervasive Al Sensors













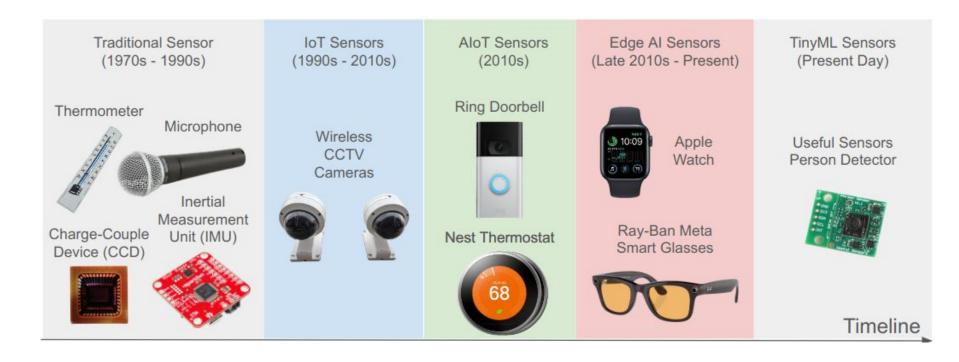
arxiv.org/abs/2402.11183



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Evolution of Sensors...



... and their impact on Responsible Al

	Traditional Sensor (1970s - 1990s)	IoT Sensors (1990s - 2010s)	AloT Sensors (2010s)	Edge Al Sensors (Late 2010s - Present)	TinyML Sensors (Present Day)
Valid and Reliable					
Safe					
Secure and Resilient					
Accountable and Transparent					
Explainable and Interpretable					
Privacy Enhanced					
Fair with Harmful Bias Managed					32

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