tinyML. EMEA

Enabling Ultra-low Power Machine Learning at the Edge

tinyML EMEA Technical Forum 2021 Proceedings

June 7 – 10, 2021 Virtual Event





INYMLPERF

Development of a Benchmark Suite for tinyML Systems

Csaba Kiraly, Digital Catapult

Colby Banbury, Harvard University





IMPORTANCE OF BENCHMARKING

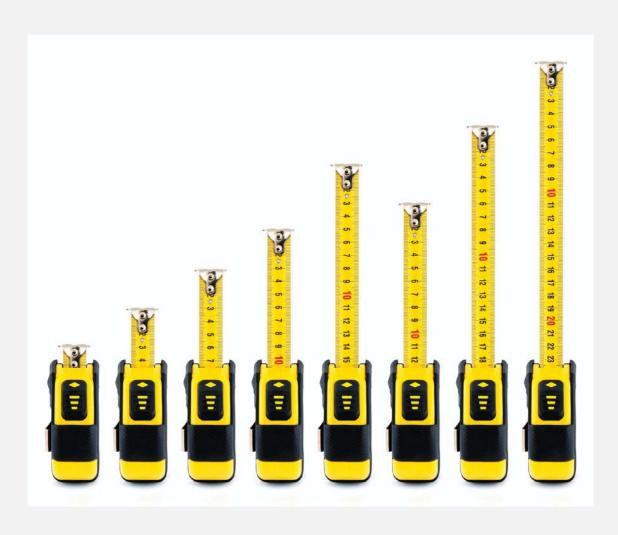




GIVEN A TASK AT HAND HOW DO WE KNOW WHICH IS THE **RIGHT SYSTEM**?

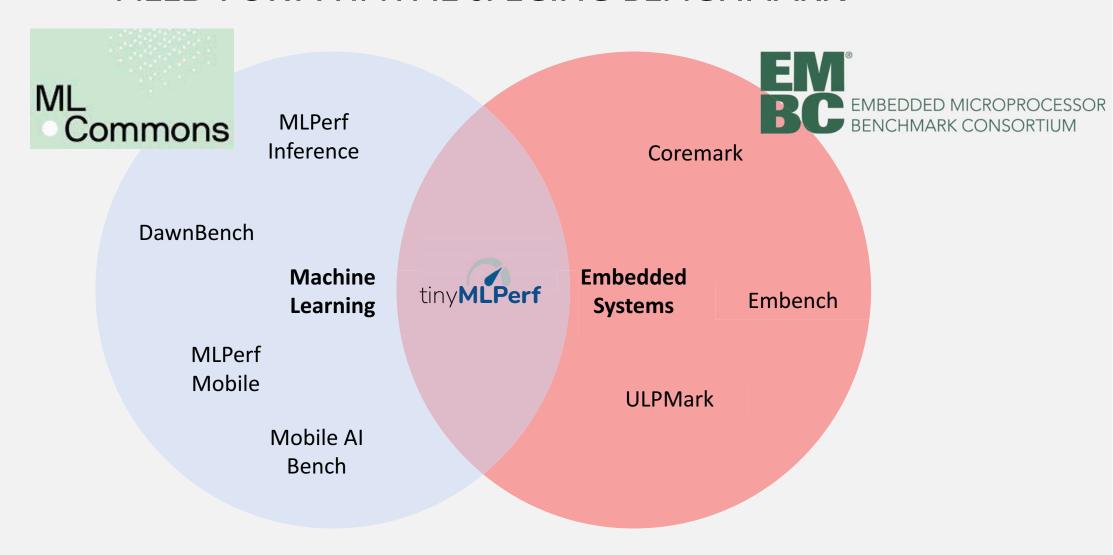
HOW DO WE **COMPARE** THE DIFFERENT SOLUTIONS?

BENCHMARKING IS ALL ABOUT ...



- Comparability across hardware and software
- Standardization of use cases and workloads
- Measuring progress via rigorous methodology
- Community building and consensus generation

NEED FOR A TINYML SPECIFIC BENCHMARK



BENCHMARK DESIGN CHALLENGES

- Number and diversity of use cases for tinyML
 - Which use cases should we focus on?
- TinyML innovation is in HW, in SW, in tooling, in algorithms, etc.
 - How do we support fair comparison and innovation?
- Embedded system design is always a compromise
 - What metrics to choose to fairly evaluate systems?

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RELEVANT USE CASES

Task Category	Use Case	Model Type
Audio	Audio Wake Words Context Recognition Control Words Keyword Detection	DNN CNN RNN LSTM
lmage	Visual Wake Words Object Detection Gesture Recognition Object Counting Text Recognition	DNN CNN SVM Decision Tree KNN Linear
Industry / Telemetry	Segmentation Anomaly Detection Forecasting Activity Detection	DNN Decision Tree SVM Linear

RELEVANT USE CASES & COMMUNITY

Task @ Harvard **Use Case Model Type** Category DNIN Audio Wake Words @ Syntiant CNN Context Recognition Audio **Control Words RNN Keyword Detection LSTM** Nat Jeffries DNN @ Google **Visual Wake Words** CIVIV **Object Detection** SVM **Image** Gesture Recognition Decision **Object Counting** KNN **Text Recognition** Linear DNN Segmentation Industry / **Anomaly Detection-**DUDIOIDIT TE Forecasting **SVM Telemetry** @ DC **Activity Detection** Linear

WG lead: Vijay Janapa Reddi + Colby Banbury

Benchmark harness: Peter Torelly @ EEMBC + Nat Jeffries @ Google

Jeremy Holleman

Pietro Montino

Csaba Kiraly



SELECTED BENCHMARKS

Keyword Spotting

Average Spectrogram < 43 values >

Warden, Pete. "Speech commands: A dataset for limited-vocabulary speech recognition." arXiv preprint arXiv:1804.03209 (2018).

Visual Wake Words



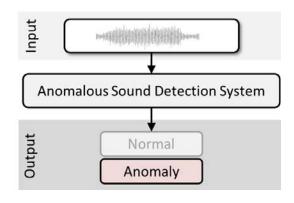
(a) 'Person'



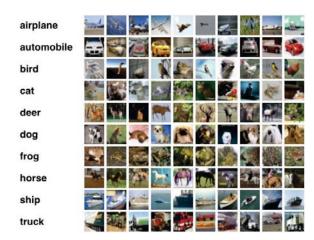
(b) 'Not-person'

Chowdhery, Aakanksha, et al. "Visual wake words dataset." arXiv preprint arXiv:1906.05721 (2019).

Anomaly Detection



Tiny Image Classification



Purohit, Harsh, et al. "MIMII dataset: Sound dataset for malfunctioning industrial machine investigation and inspection." arXiv preprint arXiv:1909.09347 (2019).

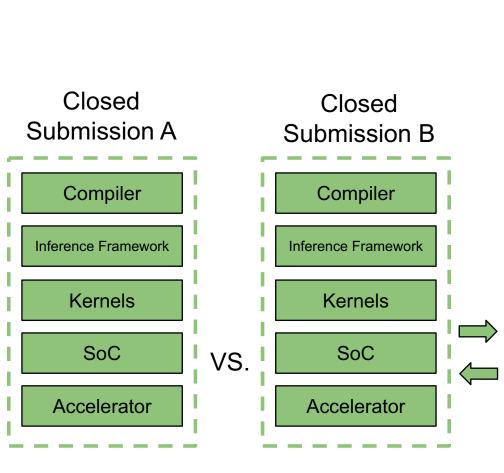
Krizhevsky, Alex, and Geoffrey Hinton. "Learning multiple layers of features from tiny images." (2009): 7.

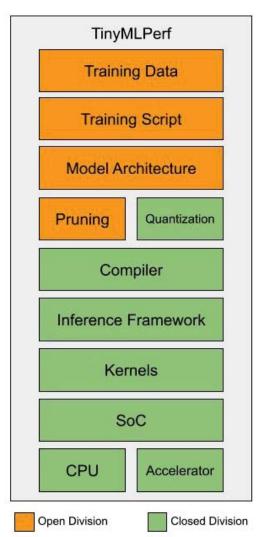
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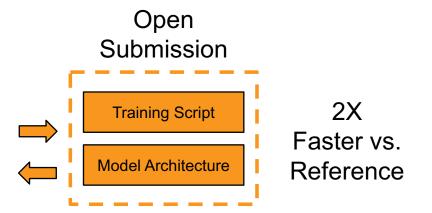
Modular Design

Direct Comparison
CLOSED DIVISION





Demonstrate Improvement OPEN DIVISION



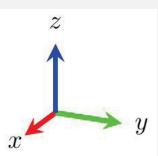
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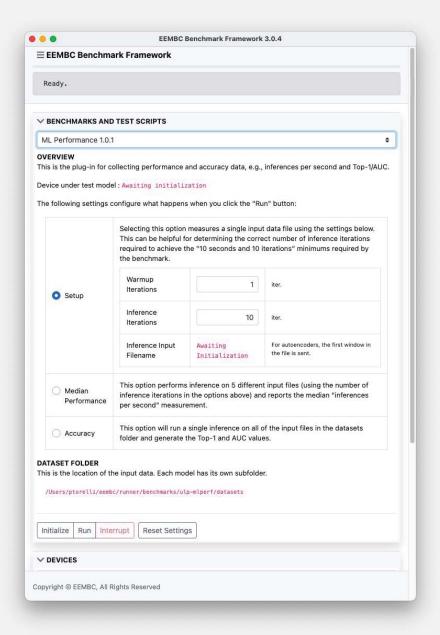
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METRICS OF INTEREST

- What metrics to choose, how to define
 - latency: ms/inference, or ms/task?
 - accuracy: which metric?
 - energy: what should be included?



- (Some) measurement difficulties
 - pre/post processing
 - single inference vs. more complex processing
 - accurate power measurement
 - accurate timestamping
- EEMBC Benchmark Runner



MEASURING THOSE METRICS

Latency

Accuracy

Energy

Accurate timestamping
Evaluated on series of inferences
Data-dependant execution?

Top-I accuracy & AUC CLOSED: meet threshold OPEN: part of the metrics

Power Monitor integration
No "cherry-picking"
Median result

Runtime requirements have been met.

Performance results for window 10:

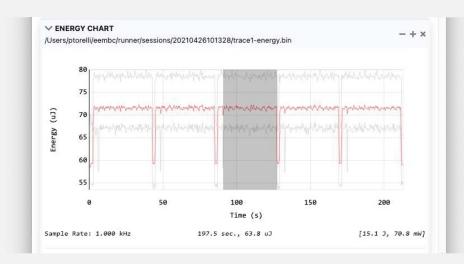
Inferences: 1000

Runtime: 10.524 sec.

Throughput: 95.020 inf./sec.

Runtime requirements have been met.

Median throughput is 95.019 inf./sec.



ALL TOGETHER: THE FULL BENCHMARK FLOW

Workgroup



Benchmark definition

Reference implementation

- Problem definition
- Dataset selection (public domain)
- Model selection / training
- Derive "Tiny" version: Quantization, etc.
- Write C implementation
- Integrate with benchmarking harness
- Deploy on device
- Benchmark
 - ML performance
 - Power consumption
- Review and Audit

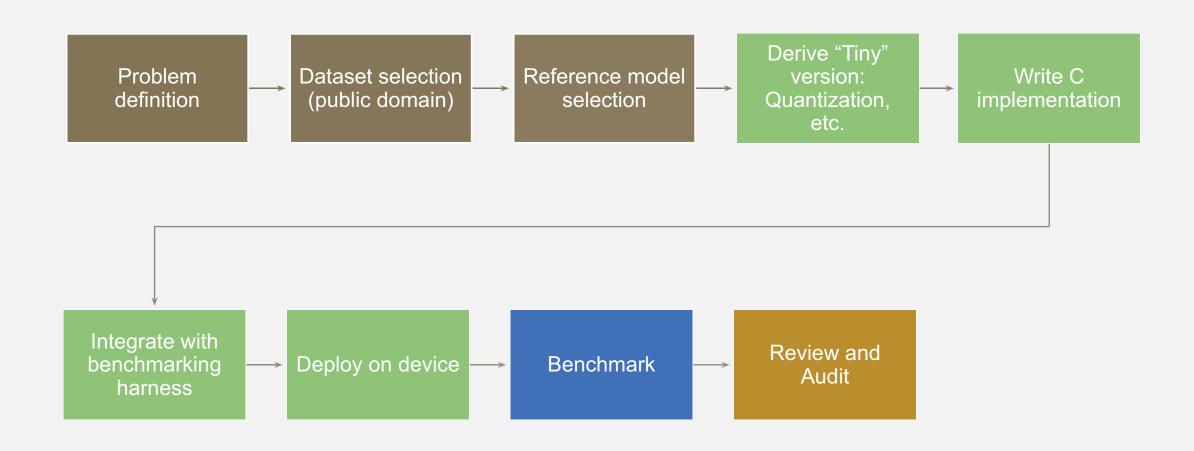
Submitter



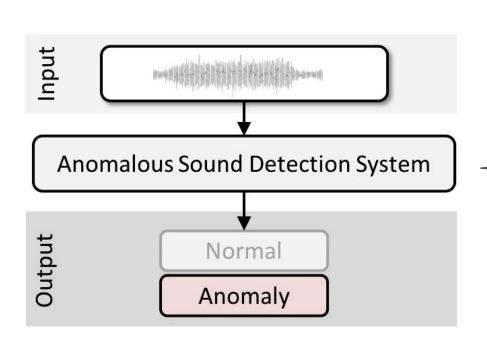
Open submission

Closed submission

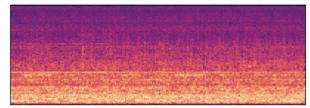
ALL TOGETHER: ANOMALY DETECTION EXAMPLE

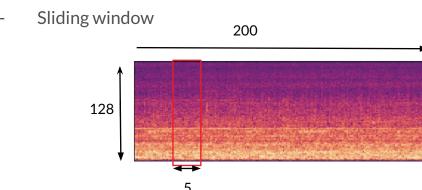


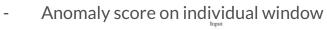
EXAMPLE: ANOMALY DETECTION



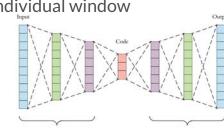








AutoEncoder



- Post-processing: average score

REFERENCE IMPLEMENTATION

ST NUCLEO-L4R5ZI













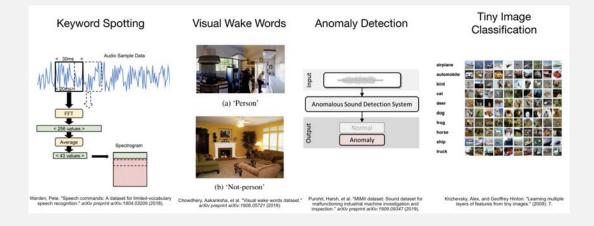
- Open platform
- Widely known, available, and affordable
- ARM Cortex-M4 with FPU
- 2 MB Flash
- 640KB SRAM

- Open source
- Portability of reference implementations



- Open source
- Full toolchain with everything we need
- Improving quantization support

TINYMLPERF: WHERE NEXT?





V0.1.0 is out bootstrapping the process

Just the beginning ...
Grow the community
Refine and define use cases
towards V0.2.0



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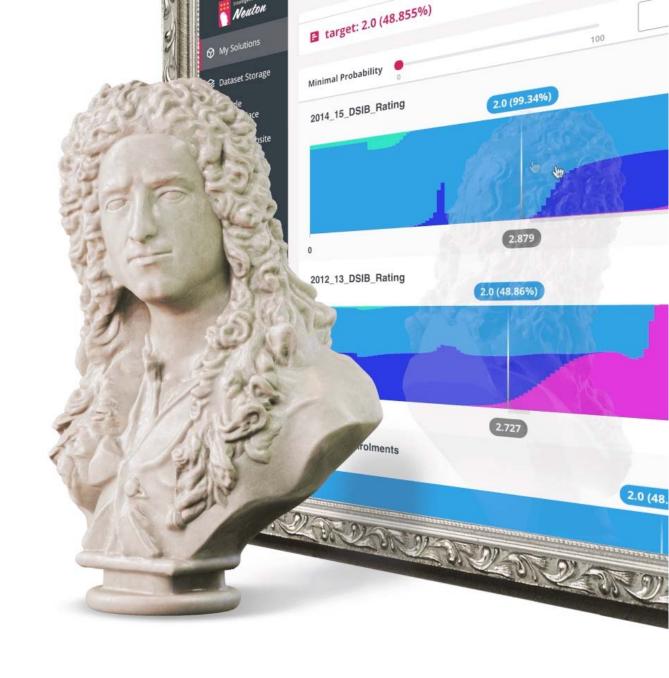
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Arm: The Software and Hardware Foundation for tinyML



Resources: developer.arm.com/solutions/machine-learning-on-arm

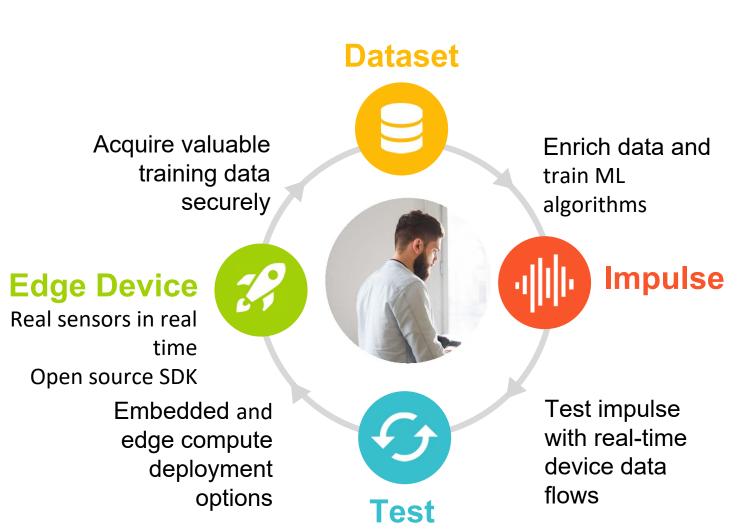


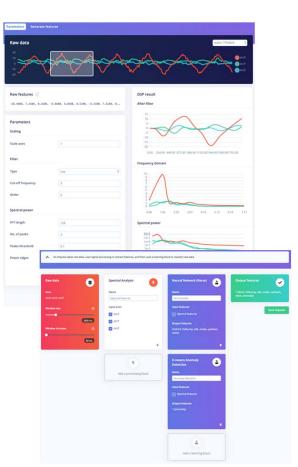
TinyML for all developers











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Advancing Al research to make efficient AI ubiquitous

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Personalization

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Efficient learning

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Reasoning

Action

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Edge cloud







Mobile

IoT/IIoT







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Founded in 2017 and headquartered in Irvine, California, the company is backed by Amazon, Applied Materials, Atlantic Bridge Capital, Bosch, Intel Capital, Microsoft, Motorola, and others. Syntiant was recently named a CES® 2021 Best of Innovation Awards Honoree, shipped over 10M units worldwide, and unveiled the NDP120 part of the NDP10x family of inference engines for low-power applications.

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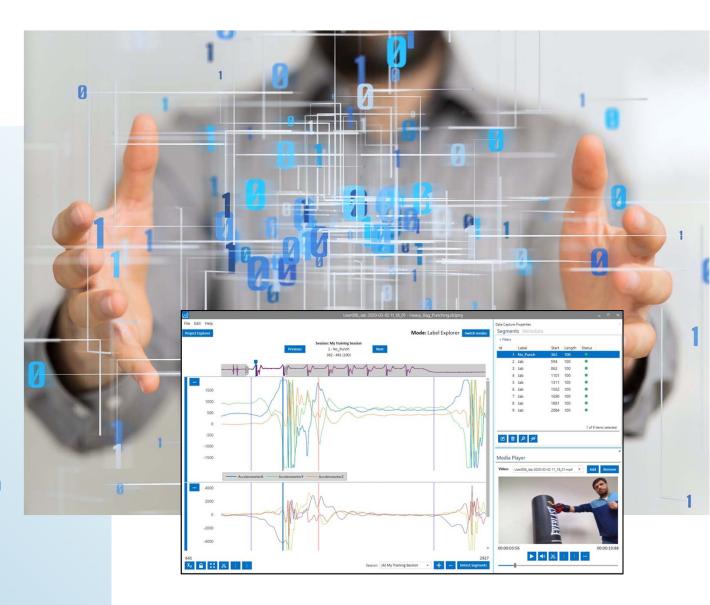


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