tinyML. Talks

Enabling Ultra-low Power Machine Learning at the Edge

"Better productivity leveraging AI community driven interoperability"

Danilo Pietro Pau- STMicroelectronics

July 20, 2021



www.tinyML.org





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TALKS webcast

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Additional Sponsorships available – contact Olga@tinyML.org for info

Arm: The Software and Hardware Foundation for tinyML



Ø @ArmSoftwareDev

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

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arm



WE USE AI TO MAKE OTHER AI FASTER, SMALLER AND MORE POWER EFFICIENT



Automatically compress SOTA models like MobileNet to <200KB with **little to no drop in accuracy** for inference on resource-limited MCUs



Reduce model optimization trial & error from weeks to days using Deeplite's **design space exploration**



Deploy more models to your device without sacrificing performance or battery life with our **easy-to-use software**

BECOME BETA USER bit.ly/testdeeplite



TinyML for all developers



www.edgeimpulse.com



The Eye in IoT Edge Al Visual Sensors

info@emza-vs.com





Computer Vision hardware accelerators

- Machine Learning algorithm
- <1MB memory footprint
- Microcontrollers computing power
- Trained algorithm
- Processing of low-res images
- Human detection and other classifiers

Enabling the next generation of Sensor and Hearable products

to process rich data with energy efficiency



Wearables / Hearables



Battery-powered consumer electronics



IoT Sensors





Distributed infrastructure for TinyML apps





Develop at warp speed

Automate deployments

Device orchestration

HOTG is building the distributed infrastructure to pave the way for AI enabled edge applications



Adaptive AI for the Intelligent Edge

Latentai.com



Maxim Integrated: Enabling Edge Intelligence

Advanced AI Acceleration IC



The new MAX78000 implements AI inferences at low energy levels, enabling complex audio and video inferencing to run on small batteries. Now the edge can see and hear like never before.

www.maximintegrated.com/MAX78000

Low Power Cortex M4 Micros



Large (3MB flash + 1MB SRAM) and small (256KB flash + 96KB SRAM, 1.6mm x 1.6mm) Cortex M4 microcontrollers enable algorithms and neural networks to run at wearable power levels.

www.maximintegrated.com/microcontrollers

Sensors and Signal Conditioning



Health sensors measure PPG and ECG signals critical to understanding vital signs. Signal chain products enable measuring even the most sensitive signals.

www.maximintegrated.com/sensors

Qeexo AutoML

Automated Machine Learning Platform that builds tinyML solutions for the Edge using sensor data

Key Features

- Supports 17 ML methods:
 - Multi-class algorithms: GBM, XGBoost, Random
 Forest, Logistic Regression, Gaussian Naive Bayes,
 Decision Tree, Polynomial SVM, RBF SVM, SVM, CNN,
 RNN, CRNN, ANN
 - Single-class algorithms: Local Outlier Factor, One Class SVM, One Class Random Forest, Isolation Forest
- Labels, records, validates, and visualizes time-series sensor data
- On-device inference optimized for low latency, low power consumption, and small memory footprint applications
- Supports Arm[®] Cortex[™]- M0 to M4 class MCUs

End-to-End Machine Learning Platform

MODE FEATURI MODEL MODEL CONVERSION ETER SPECIFIC MI EXTRACTION SELECTION VALIDATION REPROCESSING PTIMIZATION AND SELECTION (E.G. TO C) AutoML 🐞 AUTOMATED COLLECT/ UPLOAD DEPLOY/ DOWNLOAD **DEFINE PROJECT** SELECT SENSORS AND MACHINE LEARNING E.G. CLASSIFICATION TARGET HARDWARE DATA **ML PACKAGE**

For more information, visit: www.qeexo.com

Target Markets/Applications

- Industrial Predictive Maintenance
 Automotive
- Smart Home
- Wearables IoT

Mobile

Qualcom Al research

Advancing AI research to make efficient AI ubiquitous

Power efficiency

Personalization

Model design, compression, quantization, algorithms, efficient hardware, software tool

Continuous learning, contextual, always-on, privacy-preserved, distributed learning

Efficient learning

Robust learning through minimal data, unsupervised learning, on-device learning

A platform to scale Al across the industry

Perception

Object detection, speech recognition, contextual fusion

Reinforcement learning for decision making

Cloud

Edge cloud

IoT/IIoT

Automotive

Mobile

Add Advanced Sensing to your Product with Edge AI / TinyML

https://reality.ai

info@reality.ai

✓@SensorAl in Reality Al

Pre-built Edge Al sensing modules, plus tools to build your own

Reality AI solutions

Prebuilt sound recognition models for indoor and outdoor use cases

Solution for industrial anomaly detection

Pre-built automotive solution that lets cars "see with sound"

Reality AI Tools[®] software

Build prototypes, then turn them into real products

Explain ML models and relate the function to the physics

Optimize the hardware, including sensor selection and placement

Build Smart IoT Sensor Devices From Data

SensiML pioneered TinyML software tools that auto generate AI code for the intelligent edge.

- End-to-end AI workflow
- Multi-user auto-labeling of time-series data
- Code transparency and customization at each step in the pipeline

We enable the creation of productiongrade smart sensor devices.

sensiml.com

SynSense

SynSense builds sensing and inference hardware for ultra-lowpower (sub-mW) embedded, mobile and edge devices. We design systems for real-time always-on smart sensing, for audio, vision, IMUs, bio-signals and more.

https://SynSense.ai

SYNTIANT

Syntiant Corp. is moving artificial intelligence and machine learning from the cloud to edge devices. Syntiant's chip solutions merge deep learning with semiconductor design to produce ultra-low-power, high performance, deep neural network processors. These network processors enable always-on applications in battery-powered devices, such as smartphones, smart speakers, earbuds, hearing aids, and laptops. Syntiant's Neural Decision ProcessorsTM offer wake word, command word, and event detection in a chip for always-on voice and sensor applications.

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 <u>CES® 2021 Best of Innovation Awards Honoree</u>, <u>shipped over 10M</u> <u>units worldwide</u>, and <u>unveiled the NDP120</u> part of the NDP10x family of inference engines for low-power applications.

www.syntiant.com

FOUNDATION

Focus on:

(i) developing new use cases/apps for tinyML vision; and (ii) promoting tinyML tech & companies in the developer community

Submissions accepted until August 20th, 2021 Winners announced on September 1, 2021 (\$6k value) Sponsorships available: *sponsorships@tinyML.org*

Successful tinyML EMEA 2021

- Videos are available on <u>www.youtube.com/tinyML</u>
- 4 days of tinyML excitement
 - 2 tutorials
 - 5 keynotes
 - **15** tinyTalks
 - 7 lightning talks
 - 3 panel discussions & networking
 - **16** papers in the Student Forum
 - 4 partner sessions
 - **16** sponsoring companies
- 58 speakers, 1687 registered attendees!

🗖 YouTube

250 videos with 121k views

as of July 10, 2021

Next tinyML Talks

Date	Presenter	Topic / Title
Tuesday, August 3	Vikram Shrivastava, Sr. Director, IoT Marketing, Knowles Corporate	Dedicated Audio Processors at the Edge are the Future of AI

Webcast start time is 8 am Pacific time

Please contact <u>talks@tinyml.org</u> if you are interested in presenting

Reminders

Slides & Videos will be posted tomorrow

tinyml.org/forums youtube.com/tinyml

Please use the Q&A window for your questions

Danilo Pau

One year before graduating from the Polytechnic University of Milan in 1992, Danilo PAU joined STMicroelectronics, where he worked on HDMAC and MPEG2 video memory reduction, video coding, embedded graphics, and computer vision. Today, his work focuses on developing solutions for deep learning tools and applications. Since 2019 Danilo has been an IEEE Fellow. Currently serves as a member of IEEE Region 8 Action for Industry and Member of the Machine Learning, Deep Learning and AI in the CE (MDA) Technical Stream Committee IEEE Consumer Electronics Society (CESoc). With over 80 patents, 104 publications, 113 MPEG authored documents and 39 invited talks/seminars at various worldwide Universities and Conferences, Danilo's favorite activity remains mentoring undergraduate students, MSc engineers and PhD students from various universities.

Better productivity leveraging Al community driven interoperability

Danilo Pau Technical Director, IEEE & ST Fellow System Research and Applications STMicroelectronics

July 20, 2021

Global Developer Population and Demographic Study 2019, Vol 1

Source https://www.daxx.com/blog/development-trends/number-software-developers-world *https://www.stateofai2019.com/chapter-6-the-war-for-talent/#:~:text=Estimates%20of%20the%20number%20of,AI%20originated%20in%20academia.

Global Developer Population and Demographic Study 2019, Volume 1 © 2019 Evans Data Corp

Conditions for Deep Learning on MCUs

Accuracy_{neural networks} > Accuracy traditional machine learning or hand-crafted algorithm

RAM_{MCU} > Activations_{Network}

 $R0M_{MCU} > Weights_{Network}$

 $\frac{\text{NN complexity}_{\text{FLOPS}}}{\text{MCU}_{\text{FLOPS/s}}} < \frac{\text{samples in a window}}{f_{\text{sensor sampling rate/s}}}$

0

1

2

3

"Embedded Real-Time Fall Detection with Deep Learning on Wearable Devices," 2018 21st Euromicro Conference on Digital System Design (DSD), Prague, 2018, pp. 405-412, doi: 10.1109/DSD.2018.00075.

Making AI Accessible on STM32

Leader in Arm® Cortex®-M 32-bit General Purpose MCU

and on SPC58 - Chorus Family

How to bridge the AI and embedded communities?

Global Developer Population and Demographic Study 2019, Volume 1 © 2019 Evans Data Corp

The message from the embedded developer's community?

How to design and deploy resource constrained AI productively ?

Key steps for Supervised Deep Learning

life.augmented

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Interoperability

Pre-trained Neural Network models Deep Learning framework dependent

Interoperability met across levels !

STM32Cube.Al

Convert NN into optimized code for execution

X-CUBE-AI package a STM32CubeMX additional sw

life.auamented

246 operators found Abs (ONNX), ABS (TFLITE), Acos (ONNX), Acosh (ONNX), Activation (KERAS), ActivityRegularization (KERAS), Add (KERAS), Add (ONNX), ADD (TFLITE), AlphaDropout (KERAS), And (ONNX), ARG_MAX (TFLITE), ARG_MIN (TFLITE), ArgMax (ONNX), ArgMin (ONNX), ArrayFeatureExtractor (ONNX), Asin (ONNX), Asinh (ONNX), Atan (ONNX), Atanh (ONNX), Average (KERAS), AVERAGE POOL 2D (TFLITE), AveragePool (ONNX), AveragePooling1D (KERAS), AveragePooling2D (KERAS), BATCH TO SPACE_ND (TFLITE), BatchNormalization (KERAS), BatchNormalization (ONNX), Bidirectional (KERAS), Cast (ONNX), CAST (TFLITE), Ceil (ONNX), CEIL (TFLITE), Clip (ONNX), Concat (ONNX), Concatenate (KERAS), CONCATENATION (TFLITE), Constant (ONNX), Conv (ONNX), Conv1D (KERAS), Conv2D (KERAS), Conv2DTranspose (KERAS), CONV 2D (TFLITE), ConvTranspose (ONNX), Cos (ONNX), COS (TFLITE), Cosh (ONNX), Cropping1D (KERAS), Cropping2D (KERAS), CustomFloorDiv (KERAS), CustomFloorMod (KERAS), CustomPow (KERAS), CustomReshape (KERAS), CustomShape (KERAS), CustomUnpack (KERAS), Dense (KERAS), DEPTHWISE_CONV_2D (TFLITE), DepthwiseConv2D (KERAS), DEQUANTIZE (TFLITE), DequantizeLinear (ONNX), Div (ONNX), DIV (TFLITE), Dropout (KERAS), Dropout (ONNX), ELU (KERAS), Elu (ONNX), ELU (TFLITE), Equal (ONNX), EQUAL (TFLITE), Erf (ONNX), Exp (ONNX), EXP (TFLITE), EXPAND_DIMS (TFLITE), Flatten (KERAS), Flatten (ONNX), Floor (ONNX), FLOOR (TFLITE), FLOOR_DIV (TFLITE), FLOOR MOD (TFLITE), FULLY CONNECTED (TFLITE), GaussianDropout (KERAS), GaussianNoise (KERAS), Gemm (ONNX), GlobalAveragePool (ONNX), GlobalAveragePooling1D (KERAS), GlobalAveragePooling2D (KERAS), GlobalMaxPool (ONNX), GlobalMaxPooling1D (KERAS), GlobalMaxPooling2D (KERAS), Greater (ONNX), GREATER (TFLITE), GREATER_EQUAL (TFLITE), GreaterOrEqual (ONNX), GRU (KERAS), HARD SWISH (TFLITE), HardMax (ONNX), HardSigmoid (ONNX), Identity (ONNX), InputLayer (KERAS), InstanceNormalization (ONNX), KaldiNormLayer (KERAS), L2_NORMALIZATION (TFLITE), LabelEncoder (ONNX), LEAKY RELU (TFLITE), LeakyReLU (KERAS), LeakyRelu (ONNX), Less (ONNX), LESS (TFLITE), LESS EQUAL (TFLITE), LessOrEqual (ONNX), LOCAL RESPONSE NORMALIZATION (TFLITE), Log (ONNX), LOG (TFLITE), LOG_SOFTMAX (TFLITE), LOGICAL_AND (TFLITE), LOGICAL_NOT (TFLITE), LOGICAL_OR (TFLITE), LOGISTIC (TFLITE), LogSoftMax (ONNX), LpNormalization (ONNX), LRN (ONNX), LSTM (KERAS), LSTM (ONNX), LSTM (TFLITE), MatMul (ONNX), Max (ONNX), MAX_POOL_2D (TFLITE), Maximum (KERAS), MAXIMUM (TFLITE), MaxPool (ONNX), MaxPooling1D (KERAS), MaxPooling2D (KERAS), Mean (ONNX), MEAN (TFLITE), Min (ONNX), Minimum (KERAS), MINIMUM (TFLITE), MIRROR PAD (TFLITE), Mul (ONNX), MUL (TFLITE), Multiply (KERAS), Neg (ONNX), NEG (TFLITE), Not (ONNX), Or (ONNX), PACK (TFLITE), Pad (ONNX), PAD (TFLITE), PADV2 (TFLITE), Permute (KERAS), PlaceholderCustomLayer (KERAS), Pow (ONNX), POW (TFLITE), PReLU (KERAS), PRelu (ONNX), PRELU (TFLITE), QLinearConv (ONNX), QLinearMatMul (ONNX), QUANTIZE (TFLITE), QuantizeLinear (ONNX), Reciprocal (ONNX), REDUCE ANY (TFLITE), REDUCE MAX (TFLITE), REDUCE_MIN (TFLITE), REDUCE_PROD (TFLITE), ReduceL1 (ONNX), ReduceL2 (ONNX), ReduceMax (ONNX), ReduceMean (ONNX), ReduceMin (ONNX), ReduceProd (ONNX), ReduceSum (ONNX), ReduceSumSquare (ONNX), ReLU (KERAS), Relu (ONNX), RELU (TFLITE), RELU6 (TFLITE), RELU_N1_TO_1 (TFLITE), RepeatVector (KERAS), Reshape (KERAS), Reshape (ONNX), RESHAPE (TFLITE), Resize (ONNX), RESIZE BILINEAR (TFLITE), RESIZE NEAREST NEIGHBOR (TFLITE), Round (ONNX), ROUND (TFLITE), Rsqrt (ONNX), RSQRT (TFLITE), Selu (ONNX), SeparableConv1D (KERAS), SeparableConv2D (KERAS), Shape (ONNX), SHAPE (TFLITE), Sigmoid (ONNX), Sign (ONNX), Sin (ONNX), SIN (TFLITE), Sinh (ONNX), Slice (ONNX), SLICE (TFLITE), Softmax (KERAS), Softmax (ONNX), SOFTMAX (TFLITE), Softplus (ONNX), Softsign (ONNX), SPACE TO BATCH ND (TFLITE), SpatialDropout1D (KERAS), SpatialDropout2D (KERAS), SPLIT (TFLITE), Sqrt (ONNX), SQRT (TFLITE), SQUARE (TFLITE), Squeeze (ONNX), SQUEEZE (TFLITE), STRIDED_SLICE (TFLITE), Sub (ONNX), SUB (TFLITE), Subtract (KERAS), Sum (ONNX), SUM (TFLITE), SVMClassifier (ONNX), SVMRegressor (ONNX), Tan (ONNX), Tanh (ONNX), TANH (TFLITE), TensorFlowOpLayer (KERAS), ThresholdedReLU (KERAS), ThresholdedRelu (ONNX), Tile (ONNX), TILE (TFLITE), TimeDistributed (KERAS), Transpose (ONNX), TRANSPOSE (TFLITE), TRANSPOSE_CONV (TFLITE), TreeEnsembleRegressor (ONNX), UNIDIRECTIONAL SEQUENCE LSTM (TFLITE), UNPACK (TFLITE), Unsqueeze (ONNX), Upsample (ONNX), UpSampling1D (KERAS), UpSampling2D (KERAS), Xor (ONNX), ZeroPadding1D (KERAS), ZeroPadding2D (KERAS),

C:\Users\danilo pau\OneDrive - STMicroelectronics\ai>stm32ai v700 supported-ops

Neural Network Tools for STM32AI v1.5.1 (STM.ai v7.0.0-RC8)

ZipMap (ONNX)

Image: Contract of the second seco

Some advanced features

= to express developer creativity, create differentiation, your IPs Available since X-CUBE-AI v6

> = mix neural and machine learning layers Available since X-CUBE-AI v7

ONNX-ML

Dataset of sodium chloride sterile liquid in bottles for intravenous administration and fill level monitoring Journal: Data in Brief Danilo Pietro Pau; Luca Simonetta; Bipin Kumar; Prashant Namekar; Gauri Dhande, Dec 2020

Saline bottle image classification

	480MHz 2MB FLASH 1MB RAM	MACC	PARAMS	ROM KB	RAM KB	TIME/INFERENC E ms	ACCURACY
1	Baseline FP32	20,863,600	1,247,267	4.76 MB	140	NA	95.3%
2	Baseline FP32 compression=4	20,863,085	1,247,267	1.38 MB	140	212.46	same as 1
3	Baseline INT8	20,776,316	1,247,267	1.19 MB	40.94	69.6	same as 1
4	Reduced FP32	6,707,837	67,891	265.2	48.25	75.29	96%
5	Reduced INT8	6,669,699	67,891	67.11	17.53	35.9	same as 4
6	Tiny1 FP32	451,045	11,547	45.11	17.75	6.51	93.2%
7	Tiny1 INT8	451,051	11,547	11.64	8.45	2.43	same as 6
8	Tiny1DW FP32	253,384	9,419	35.67	18.12	3.84	90.84%
9	Tiny1DW INT8	246,772	9,131	9.46	9.65	1.55	-0.43 vs 8
10	Tiny2 FP32	396,625	7,671	29.96	17.75	6	92.1%
11	Tiny2 INT8	387,687	7,671	7.75	8.37	2.3	+0.43 vs 10
12	Tiny3 Sep FP32	342,749	4,910	19.5	35	6.7	93.5%
13	Tiny3 Sep INT8	342,755	4,910	5.5	9.64	2.63	-0.44 vs 12
14	Tiny4 Sep FP32	43,672	1,126	4.57	12.2	1.4	84.55%
15	Tiny4 Sep INT8	39,023	1,126	1.46	3.16	0.821	same as 14

16

Affordable POC for early IoT practitioners

- Attach a MUCLEO-STM32 to the laptop:
 - STM32 MCU runs the model generated with X-CUBE-AI «validation on target» app
 - Image Sensor is attached to PC (webcam), python script reads sensor data and sends to the NUCLEO-STM32, which process and send back results to GUI
 - Communication through a serial port emulated on USB
 - Data information is encoded on PC with the STM32 binary protocol and decoded on

Affordable POC for early IoT STM32H7 practitioners

		WWW.BANDICAM.COM					
				ST Tutorial on Tiny Neural Network	- 🗆 X		
nstrator on Tiny Neura	al Network: Test Results		- 🗆 X	ST Tutorial on Tir	y Neural Network		
lmage n° 1	Predicted Class bottle full			with STM32Cube.AI on	STM32 Microcontroller		
		Model time efficiency					
					STM32		
				life.augmented	Cube Al		
		Inference time : 3.835 ms/Image			ouso./ li		
				Danil Alessan	o Pau dro Carra		
		Classification of the outputs		V2	2.0.1		
		bottle full : 1 Images		tiny 1dw	Refresh NN and camera		
			Capturing		- 0 X		
		bottle 80% : 0 Images			Camera		
		bottle 50% : 0 Images	and the second				
			1000				

Affordable POC for early IoT STM32F3 practitioners

lmage n° 1	Predicted Class bottle 50%		
		Model time efficiency	STM32
		Inference time : 325.722 ms/Image	red Cube .Al
		Classification of the outputs	Danilo Pau Alessandro Carra V2.0.1
		bottle full : 0 Images	Select label file
		bottle 80% : 0 Images	Select image Select Validation File
		bottle 50% : 1 Images	j, incr
			300-

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(Tiny) Function Packs

Simple, fast, optimized

STM32 Embedded Software Packages

Part Number	Manufacturer	Description
<u>X-LINUX-AI</u>	ST	STM32 MPU OpenSTLinux Expansion Pack for AI computer vision application
FP-AI-SENSING1	ST	STM32Cube function pack for ultra-low power IoT node with artificial intelligence (AI) application based on audio and motion sensing
FP-AI-VISION1	ST	STM32Cube function pack for high performance STM32 with artificial intelligence (AI) application for Computer Vision
FP-AI-NANOEDG1	ST	Artificial Intelligence (AI) condition monitoring function pack for STM32Cube
FP-AI-FACEREC	ST	Artificial Intelligence (AI) face recognition function pack for STM32Cube
FP-AI-CTXAWARE1	ST	STM32Cube function pack for ultra-low power context awareness with distributed artificial intelligence (AI)

https://www.st.com/content/st_com/en/ecosystems/stm32-ann.html

Context awareness: <u>https://www.youtube.com/watch?v=I_XqYFci5PE</u>

FP-AI-CXTAWARE1: the best power system saving solution

FP-AI-NANOEDG1

Step 1 : (PC Side) Creation of an ANOMALY DETECTION Machine Learning library

Step 2 : **(MCU Side)** Use of an ANOMALY DETECTION Machine Learning library

In just a few steps, create a machine learning library*, custom to your project, and based on a small amount of data captured using your sensor.

PC (Win/Linux)

*A NanoEdge AI Machine Learning Library is a self learning engine, that will train a ML model, inside the Microcontroller and based on locally acquired data/signal. Each library learns the engine on which it is placed and then analyses it by comparing the learning done locally with the new signals that are coming.

NanoEdge Al by Cartesiam

NanoEdge AI is a static AI library for embedded c software running on any Arm Cortex MCU

Learning and inference done at the edge.

No pre-trained neural network needed

All work (learning and inference) executed inside the STM32 MCU

AI beyond autonomous-driving

Multiple scenarios

Electrification

- Battery Management: State of Health and Charge
- Hybrid: Efficient Propulsion Mix
- Transmission: Improved Torque Control

Predictive Maintenance

- Early Detection of anomalies
- Dynamic recalibration to improve robustness

In-Cabin Behaviour Monitoring

- Emergency conditions: Drowsiness, Illness, "Backseat Child"
- Adaptive Comfort settings & driving mode (Sport / Eco)
- Driver identification and monitoring

Vehicle Security

- Hacking, Malicious Attacks
- Physical Vehicle Tampering

Sensor Augmentation

- NOx emission prediction
- Virtual sensors (Vehicle Attitude)
- Sensor degradation compensation

life auament

- OpenSource IDE based on ECLIPSE
- Full MISRA 2012 compliant register level access (RLA) low level drivers
- MISRA 2012 checking for customer code
- Visual MCU's pins configuration, run modes and full clock tree configuration with automatic constraints checking
- FreeRTOS support
- Software examples for discovery kits and premium evaluation boards covering most used peripherals
- Compilers: GCC, GHS (green hills software), HighTec EDV-System
- Artificial Intelligence plug-in; generated software easily portable across different boards

1)	Intrusion detection	

- 2) Battery charge prediction
- 3) Battery lifetime prediction
- 4) Audio de-noising

Battery Management with Long Short-Term Memory (LSTM) Example Neural Net provided with SPC5 Studio.AI

Actual Performance on Chorus family of automotive MCUs

Device	Flash used (kB)	RAM used (kB)	Inference time (ms)
SPC584B 1 (of 1) z4 core @120MHz	149.05	6.66	6.3791
SPC58EC 1 (of 2) z4 @180MHz	152.35	6.79	4.3906
SPC58EG 1 (of 3) z4 @180MHz	154.46	6.91	4.398
SPC58NH 1 (of 3) z4 @200MHz	153.98	6.85	3.7923

Dataset http://ti.arc.nasa.gov/project/ prognostic-datarepository.

* EVs acceptable SoH error range

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SPES

Thank you

danilo.pau@st.com

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