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- NVIDIA's Edge AI and Robotics Teaching Kit
- Harvard - TinyML Courseware and Machine Learning Systems
- MIT - TinyML and Efficient Deep Learning Computing
- Dive into Deep Learning and Luis Serrano's Academy and his books and videos
- IoT Fundamentals: Networking Technologies, Protocols, and Use Cases for the Internet of Things, 2017 by David Hanes
- Introduction to IoT, 2021 by Anandarup Mukherjee; *AI at the Edge* by Daniel Situnayake, Jenny Plunkett - O'Reilly

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CP 330

Edge AI

Lecture 1: Introduction

Pandarasamy Arjunan (Samy)
Assistant Professor
Robert Bosch Centre for Cyber Physical Systems
Indian Institute of Science, Bengaluru
samy@iisc.ac.in
https://www.samy101.com/edge-ai-26/

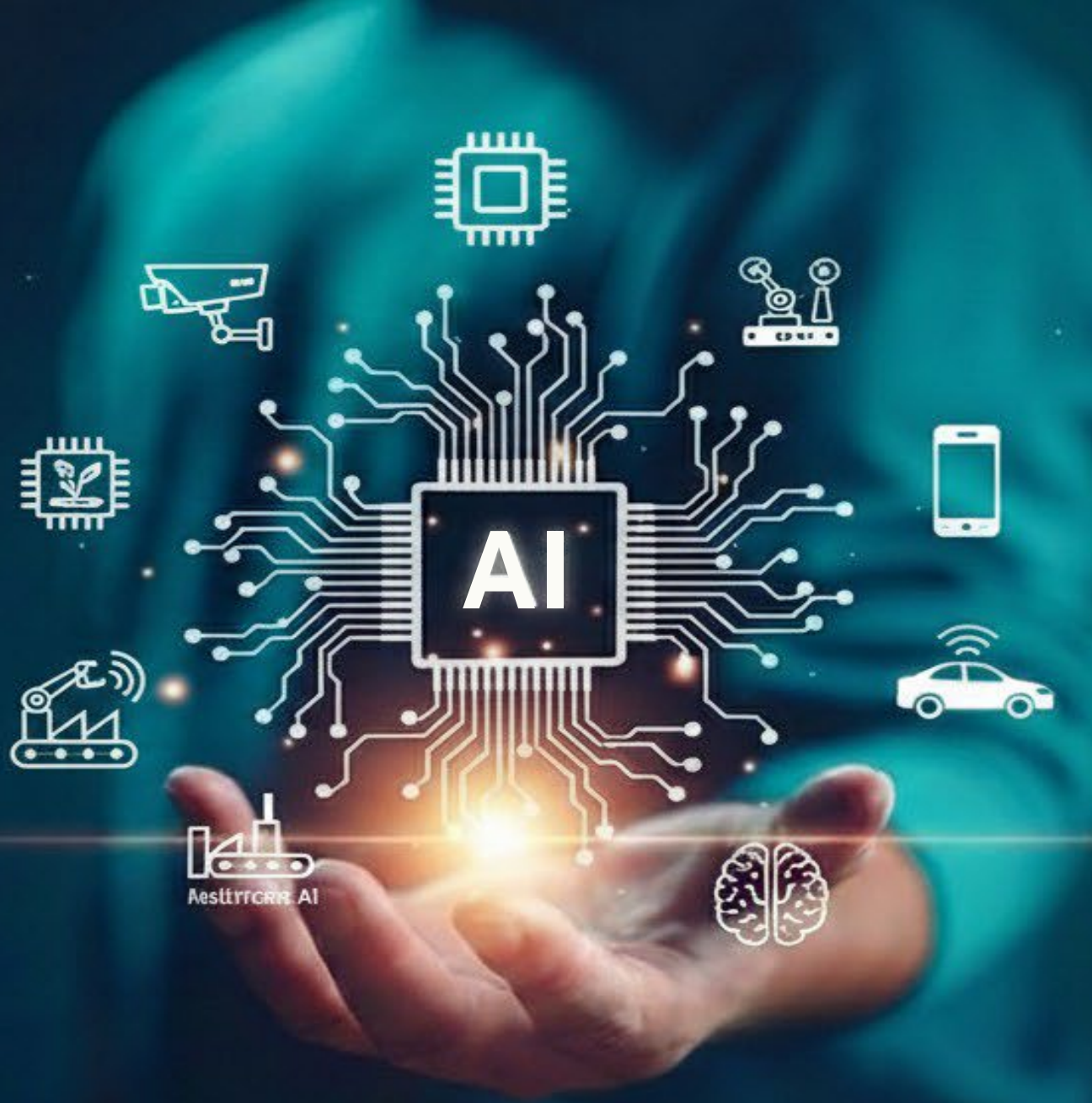


Image source: https://leverx.com

Career (Academic and Industry):

- Assistant Professor, IISc, Bangalore (Since July 2023)
- Postdoc Scholar, BEARS, UC Berkely's Lab in Singapore (2018-2023)
- Data Scientist (DataGen and SenSing) (2017-2018)
- IBM Research (Fellowship and Internship), Bangalore (2014-2015)
- Visiting Graduate Researcher, NESL @ UCLA (2013)
- PhD Scholar, IIIT-Delhi

Research Interests and Expertise:

- IoT, CPS, AI/ML and Edge AI
- Domains: Smart X (Energy, Buildings, Cities, Mobility, and Agri)

More details at https://www.samy101.com/

IIIT-D IBM Research BEARS Berkeley Education Alliance for Research in Singapore Limited

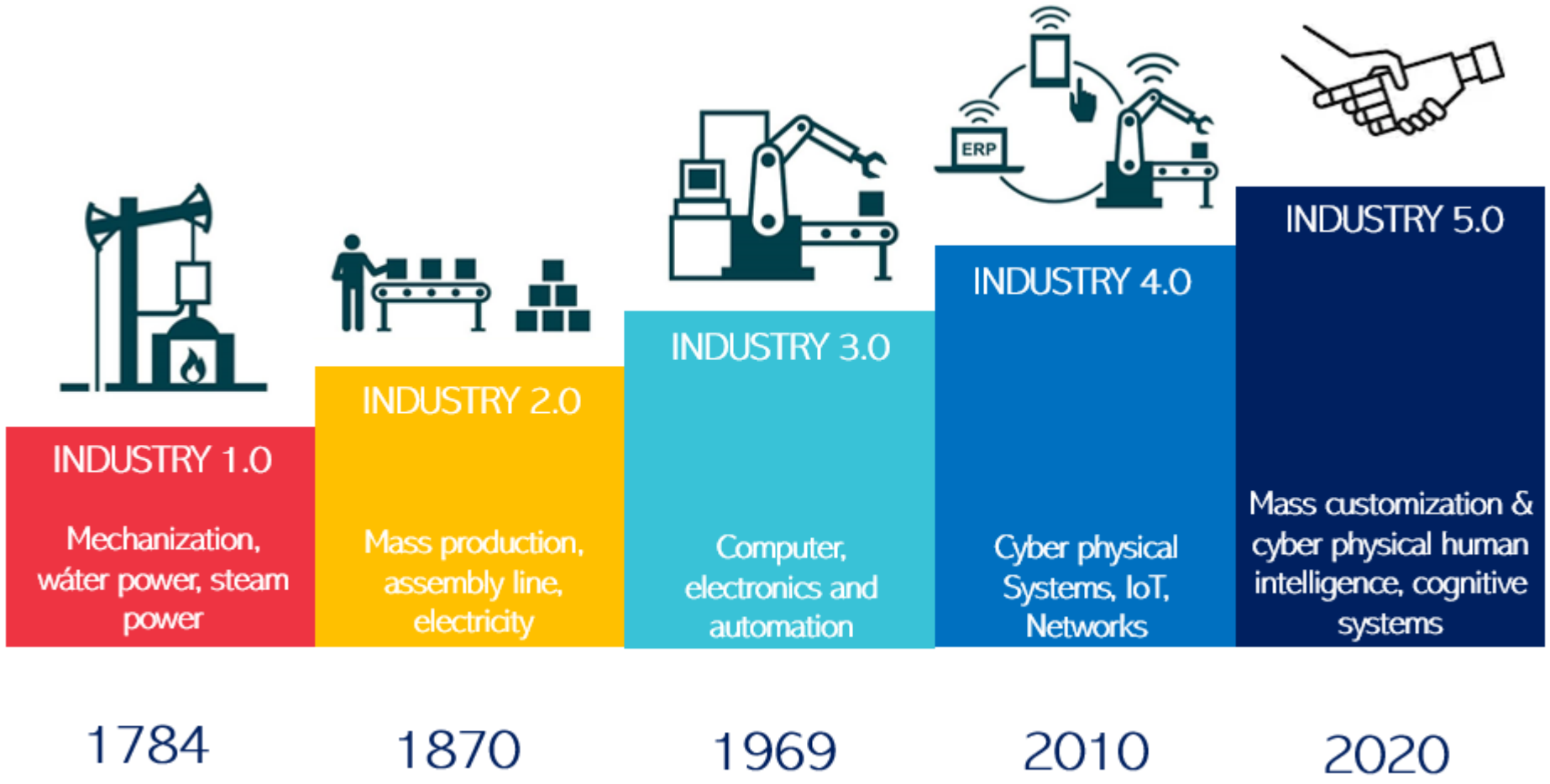
UCLA Berkeley University of California SinBerBEST²

Building Efficiency and Sustainability in the Tropics

Course Logistics

- Lecture
  - Mondays 5:30 to 7 PM
  - G22 Seminar Hall, IDR Building
- Lab Sessions
  - Wednesdays 5:30 to 7 PM
  - #205, IDR
- Teams code: gv8tpy0
- Course website: https://www.samy101.com/edge-ai-26/

Industrial Revolution



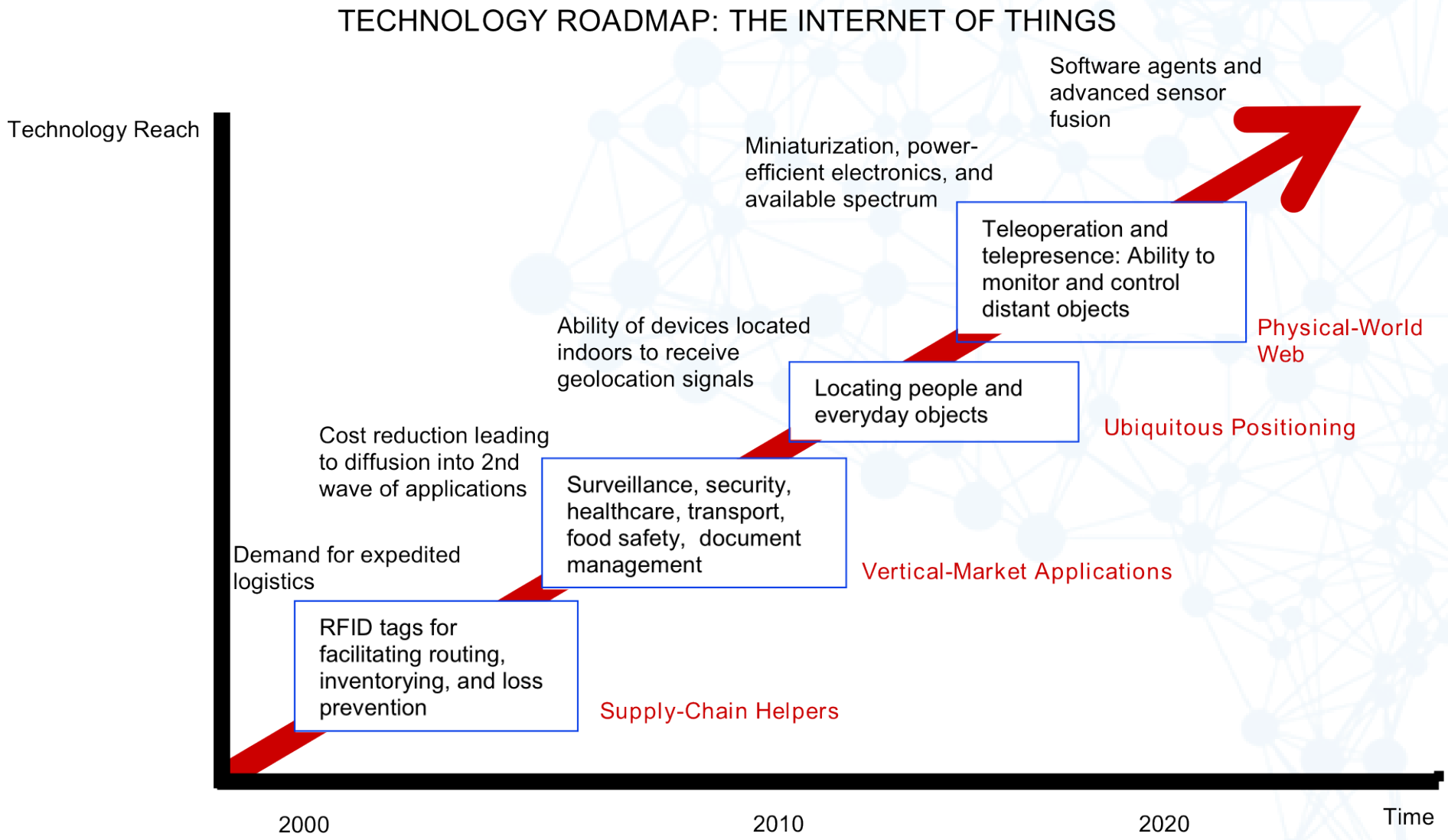
*Years are estimates

Source: Internet

What is Internet of Things (IoT)?

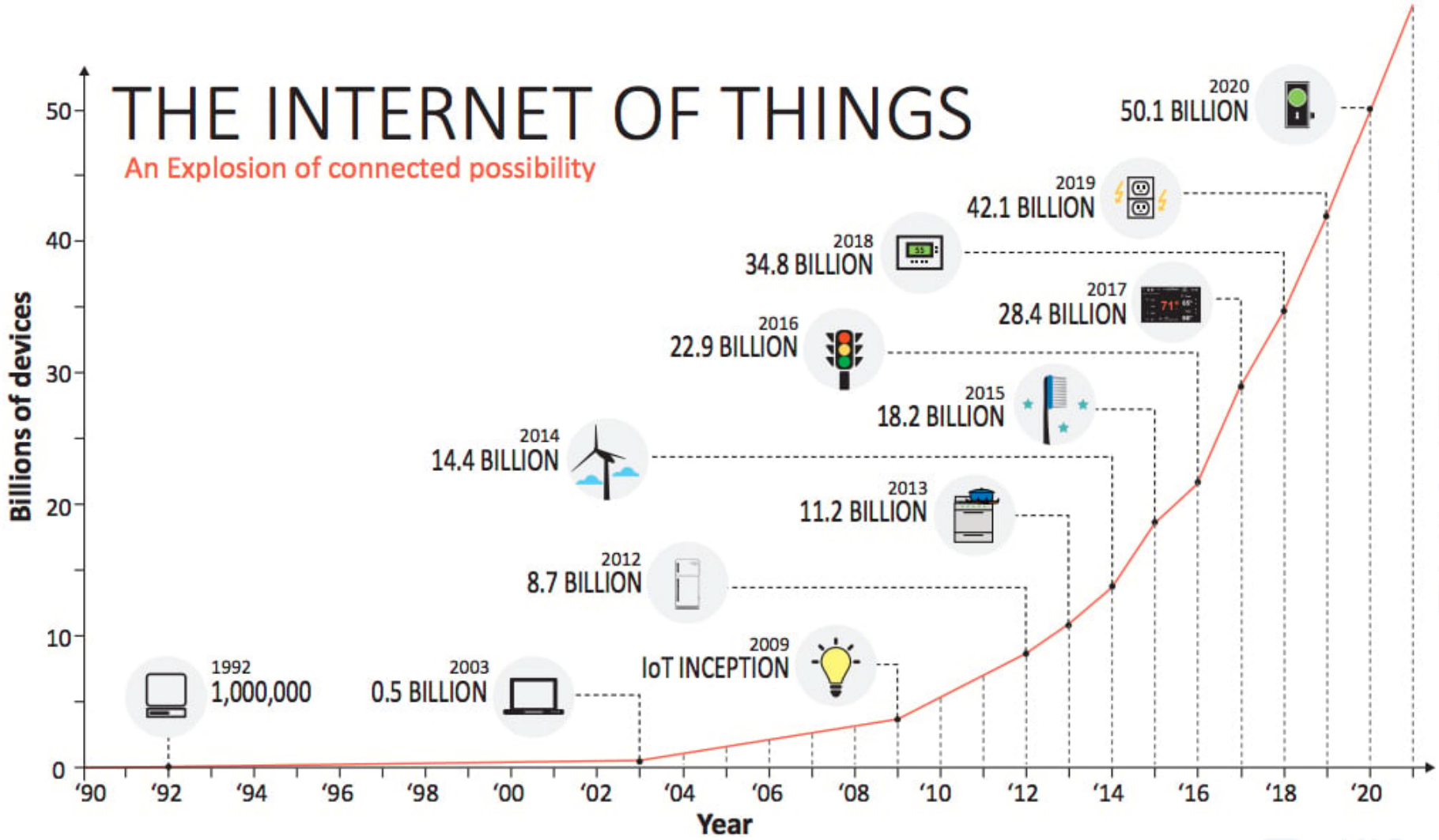
IoT is a network of physical objects that are embedded with sensors, software, and network connectivity, allowing them to collect, exchange, and act on data over the internet.

IoT Evolution



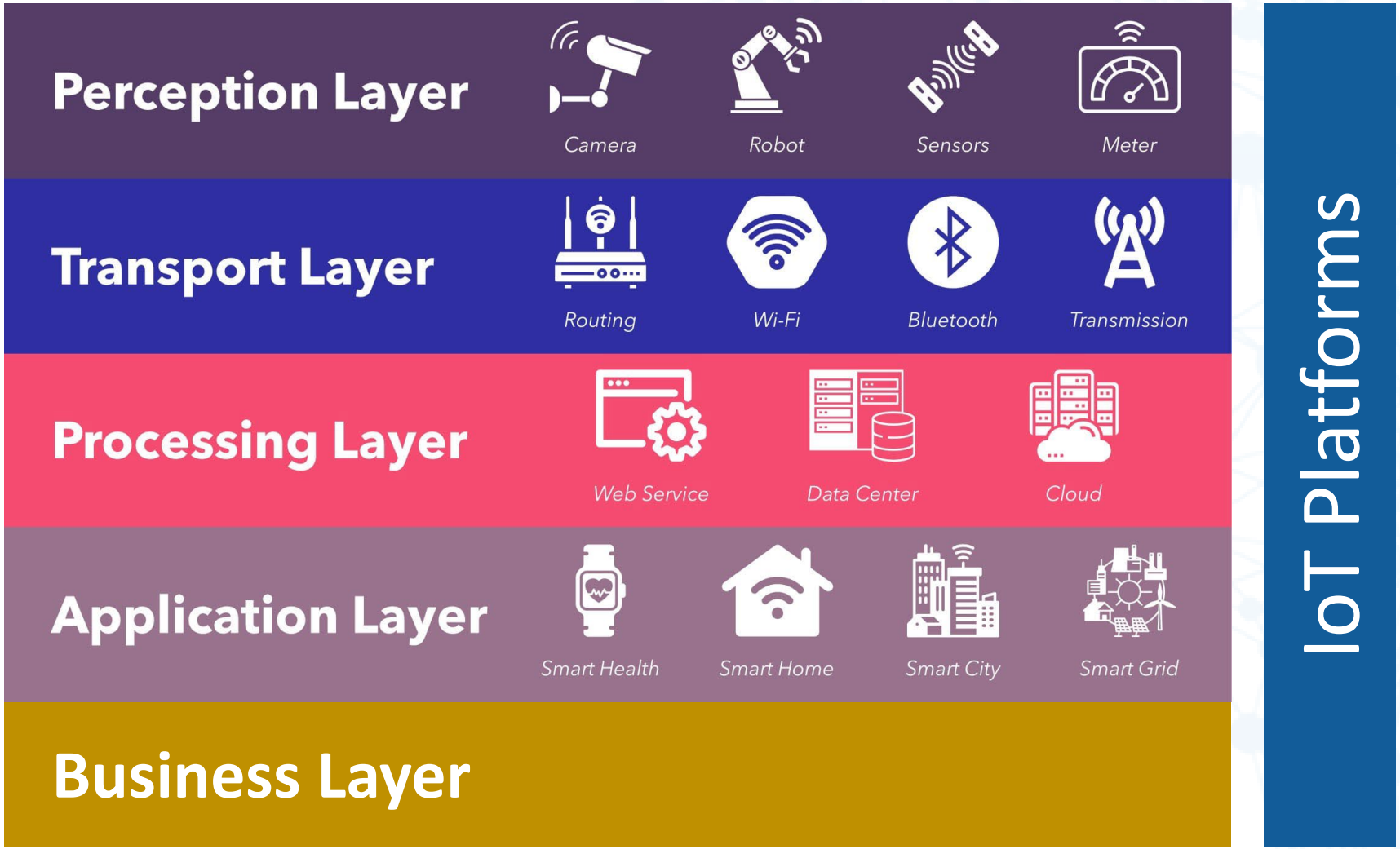
Source: SRI Consulting Business Intelligence

IoT Evolution



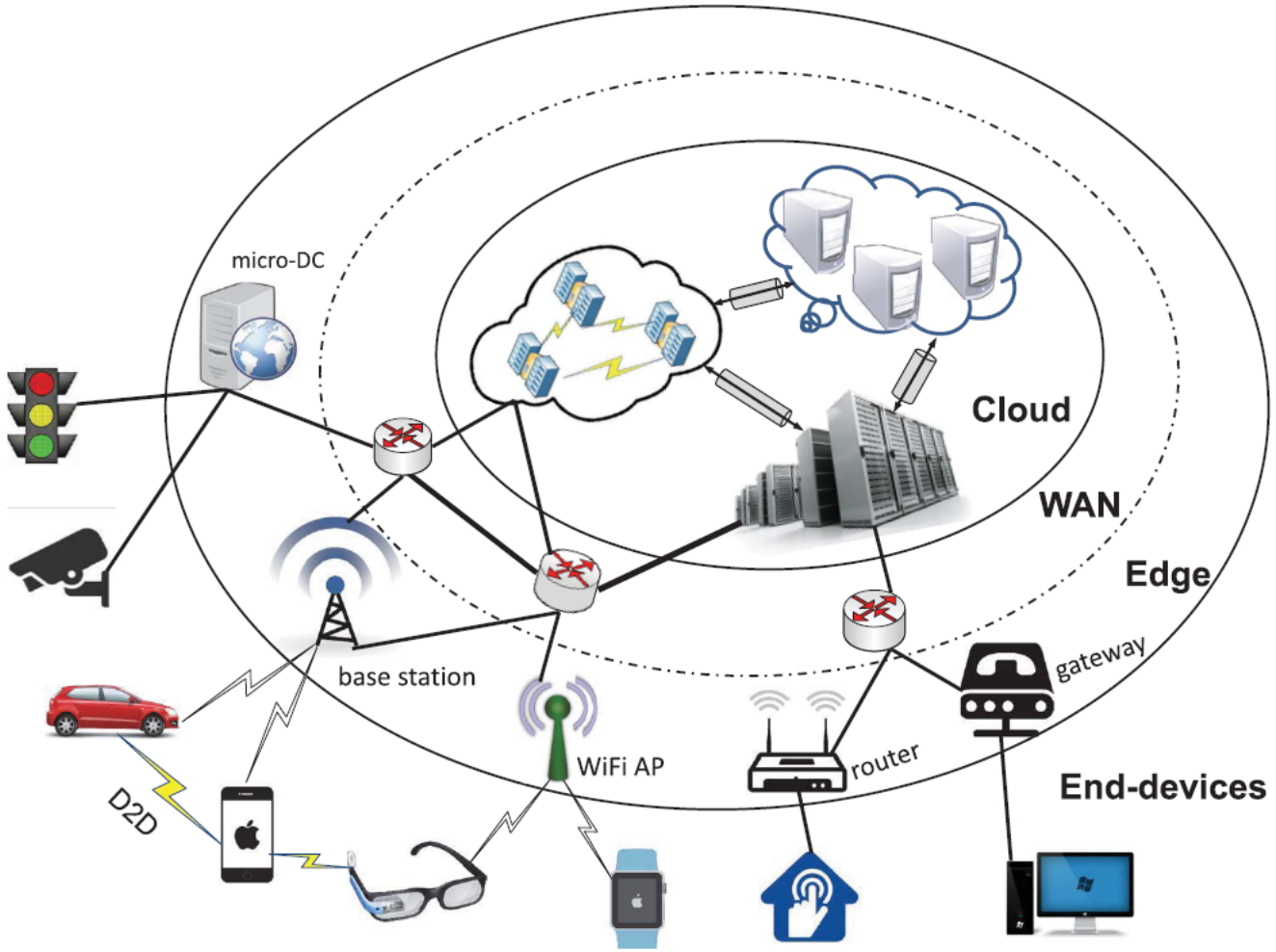
Source: Internet

IoT Architecture and Layers



Source: https://dgtlinfra.com/

IoT and Edge Devices



Edge Devices

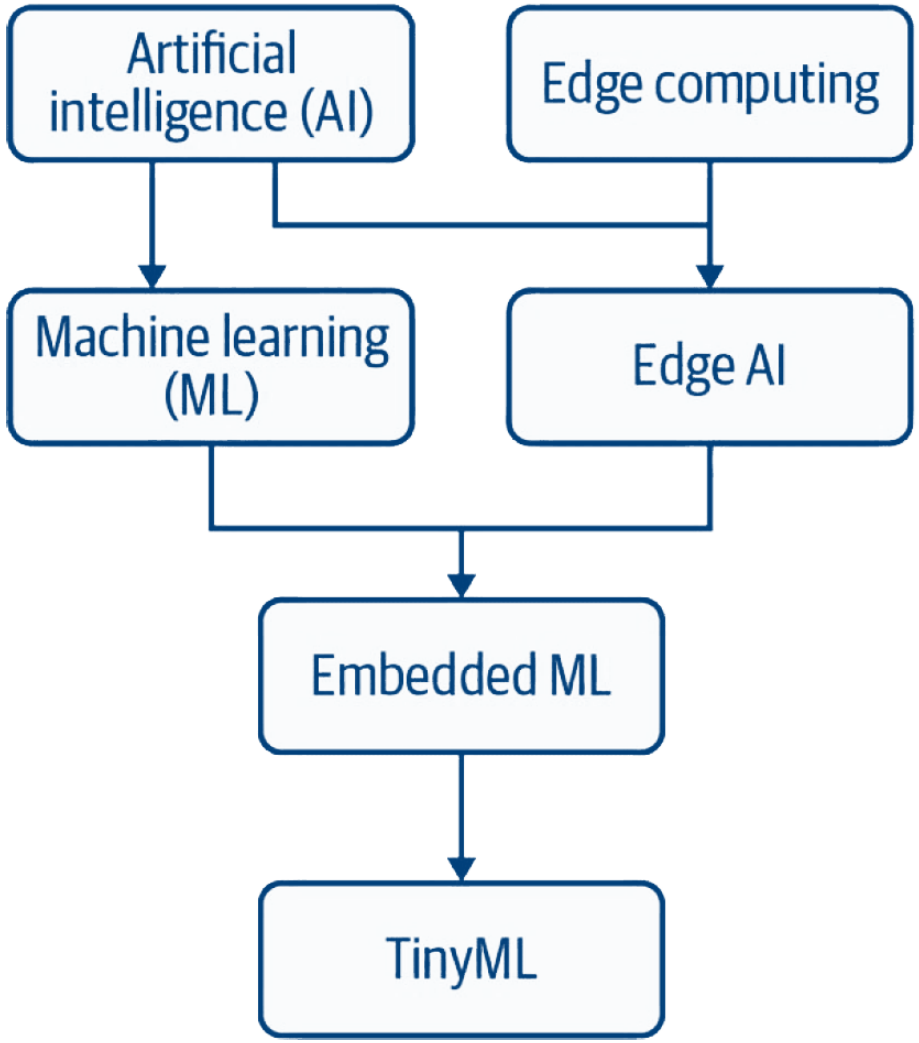
- Provide connectivity between end devices and cloud services
- Deployed close to data sources to enable low-latency processing
- Operate under limited compute, memory, and energy budgets

Edge Computing

- Processes data close to where it is generated (at the network edge), rather than relying solely on centralized cloud data centers
- Reduces latency and bandwidth usage
- Enables real-time processing and decision-making
- Improves privacy, reliability, and energy efficiency

Source: Edge Intelligence: Paving the Last Mile of Artificial Intelligence With Edge Computing (Zhou et al. 2019)

The BIG picture of Edge AI



Processing data near the data source instead of sending it to the cloud.

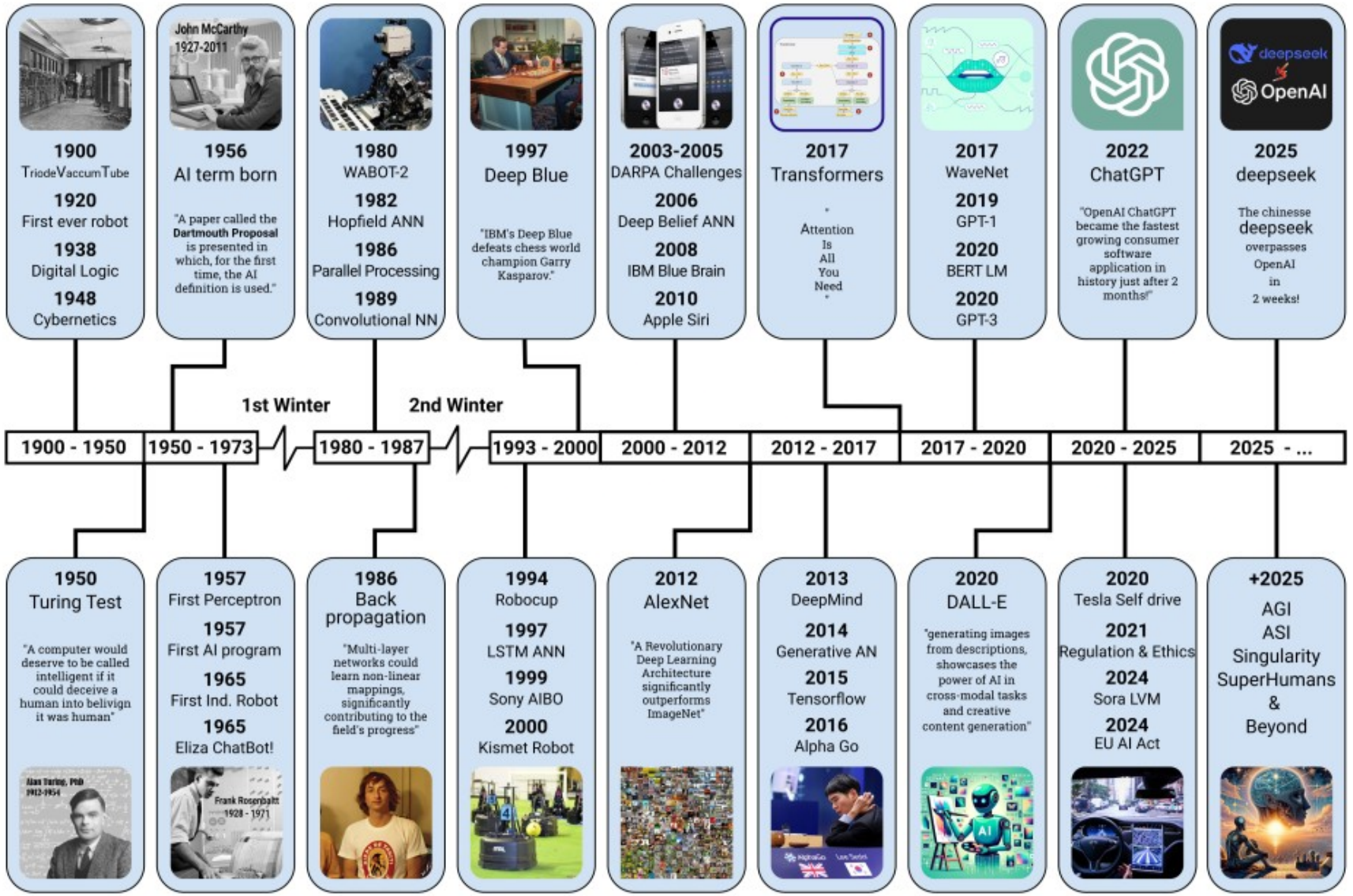
Executing and adapting AI models on edge devices, enabling local intelligence without reliance on the cloud.

Running ML models on resource-constrained embedded systems

Ultra-low-power ML on microcontrollers with extremely limited resources

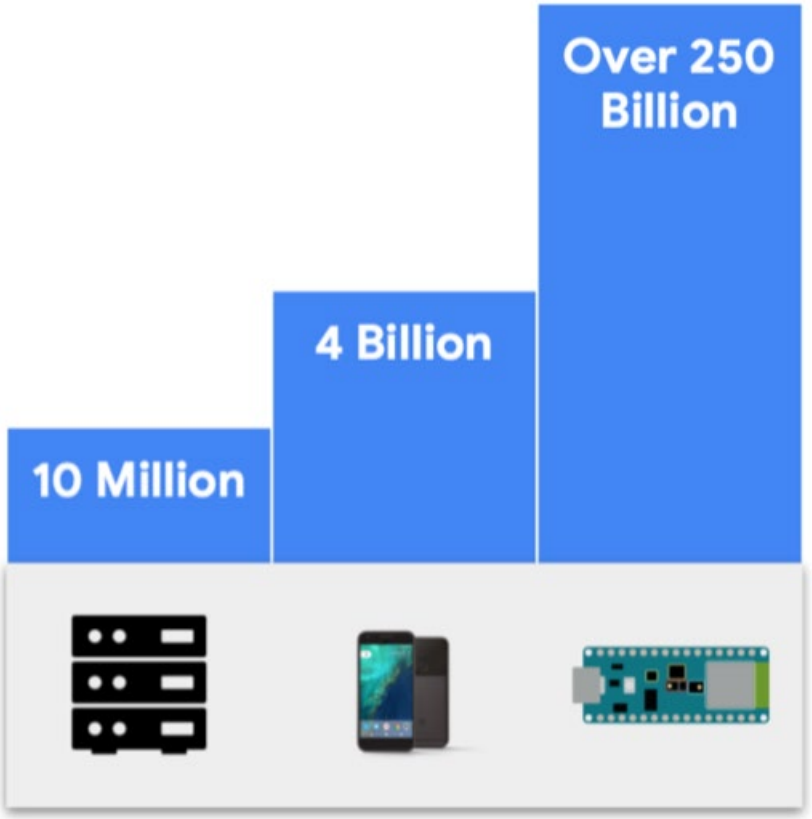
Source: [3]

Evolution of AI



Source: https://en.wikipedia.org/wiki/Timeline_of_artificial_intelligence

Most Intelligence will be on-device!



5 Quintillion

bytes of data produced every day by IoT

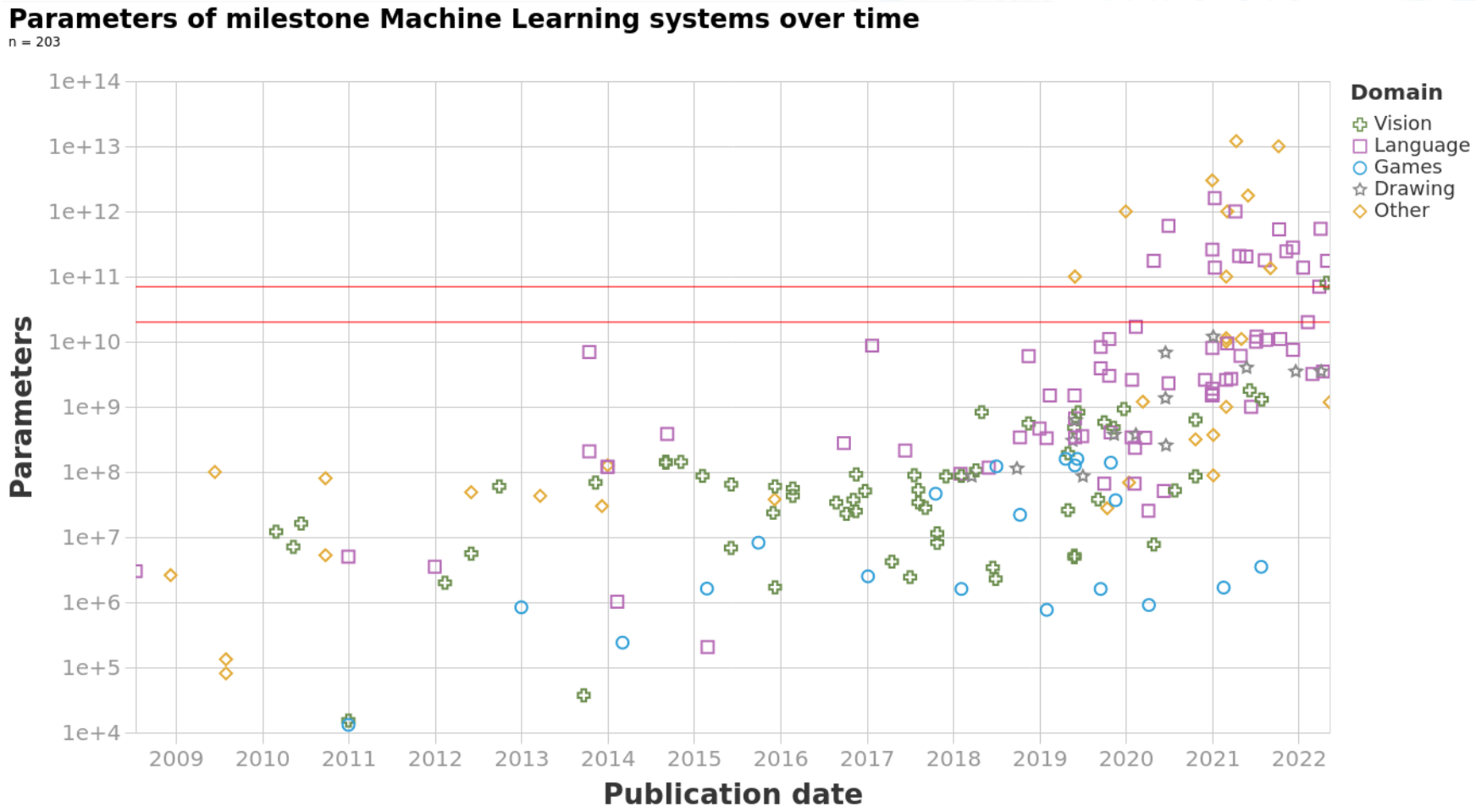
<1%

of unstructured data is analyzed or used at all

Source: Harvard Business Review, What's Your Data Strategy?, April 18, 2017
Cisco, Internet of Things (IoT) Data Continues to Explode Exponentially. Who Is Using That Data and How?, Feb 5, 2018

AI Model Size

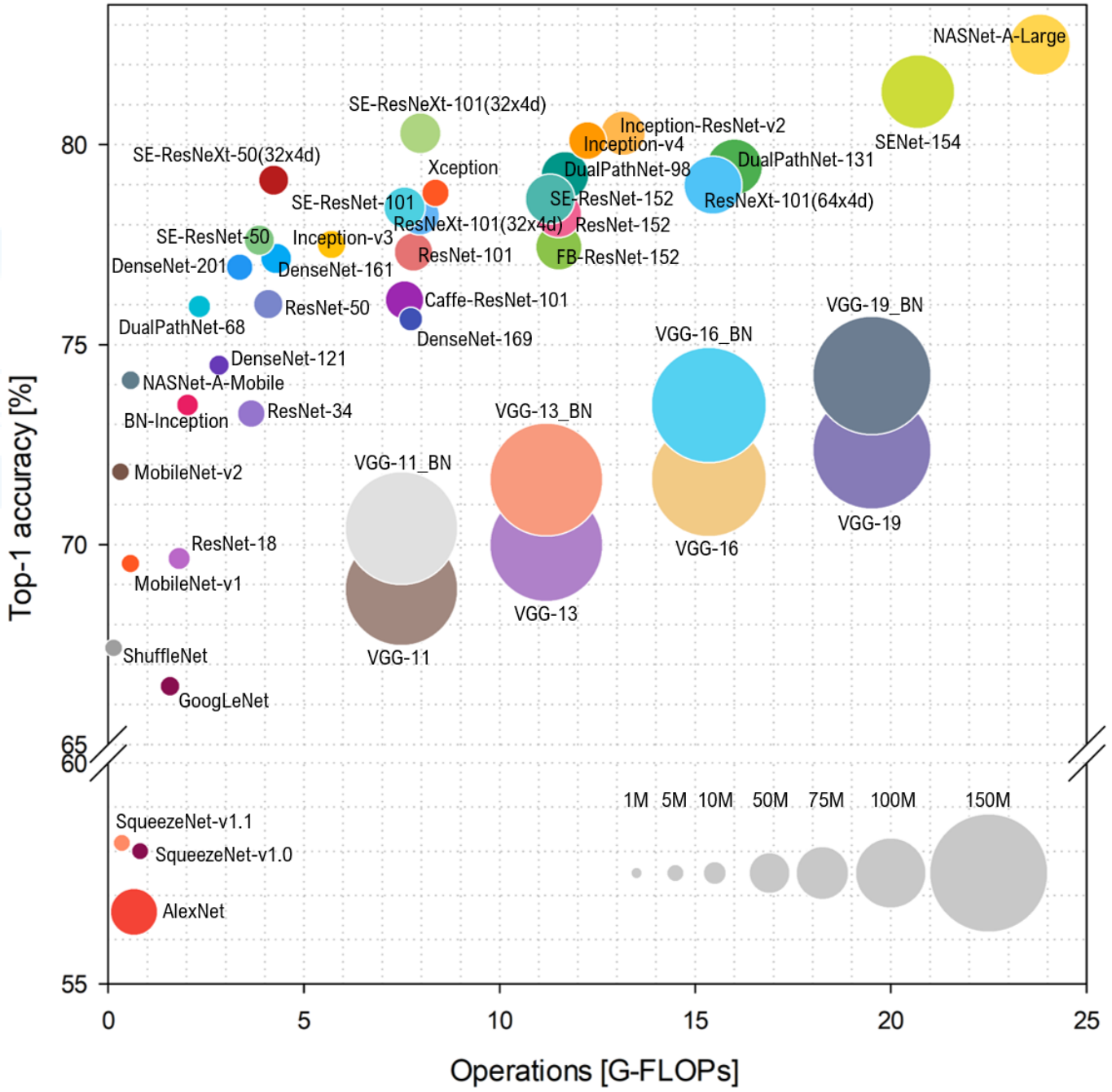
ML Model size has grown 10x faster than before since 2018



Source: https://epoch.ai/ and Machine Learning Model Sizes and the Parameter Gap (Villalobos et al., 2022)

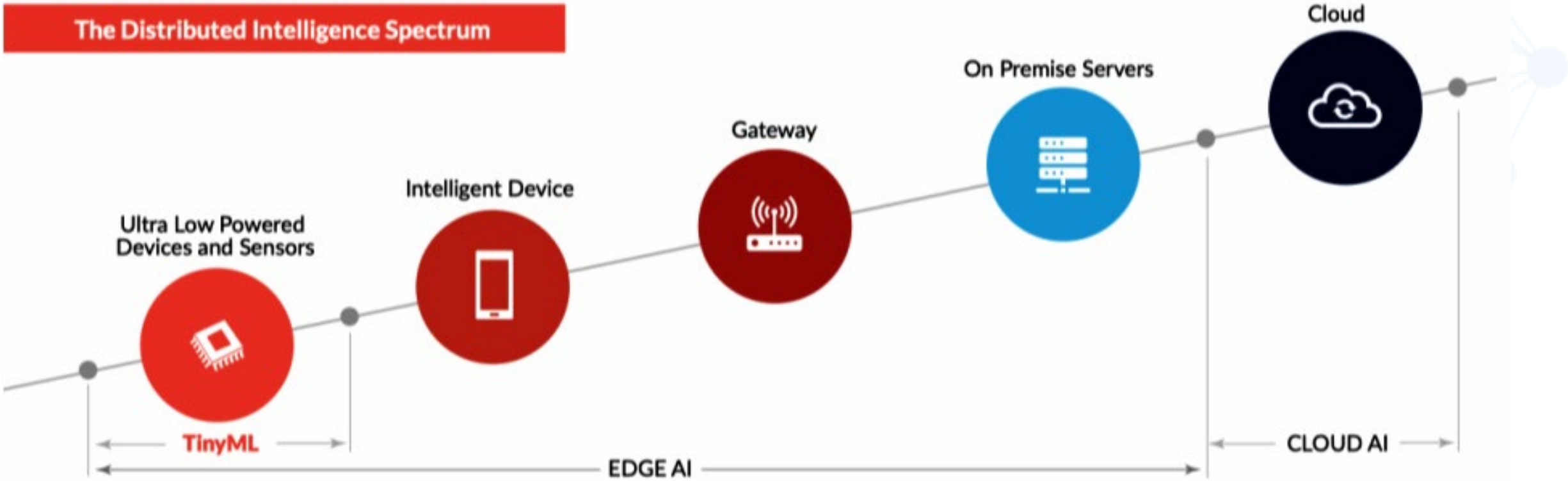
AI Model Size

Top-1 accuracy vs. computational complexity on ImageNet



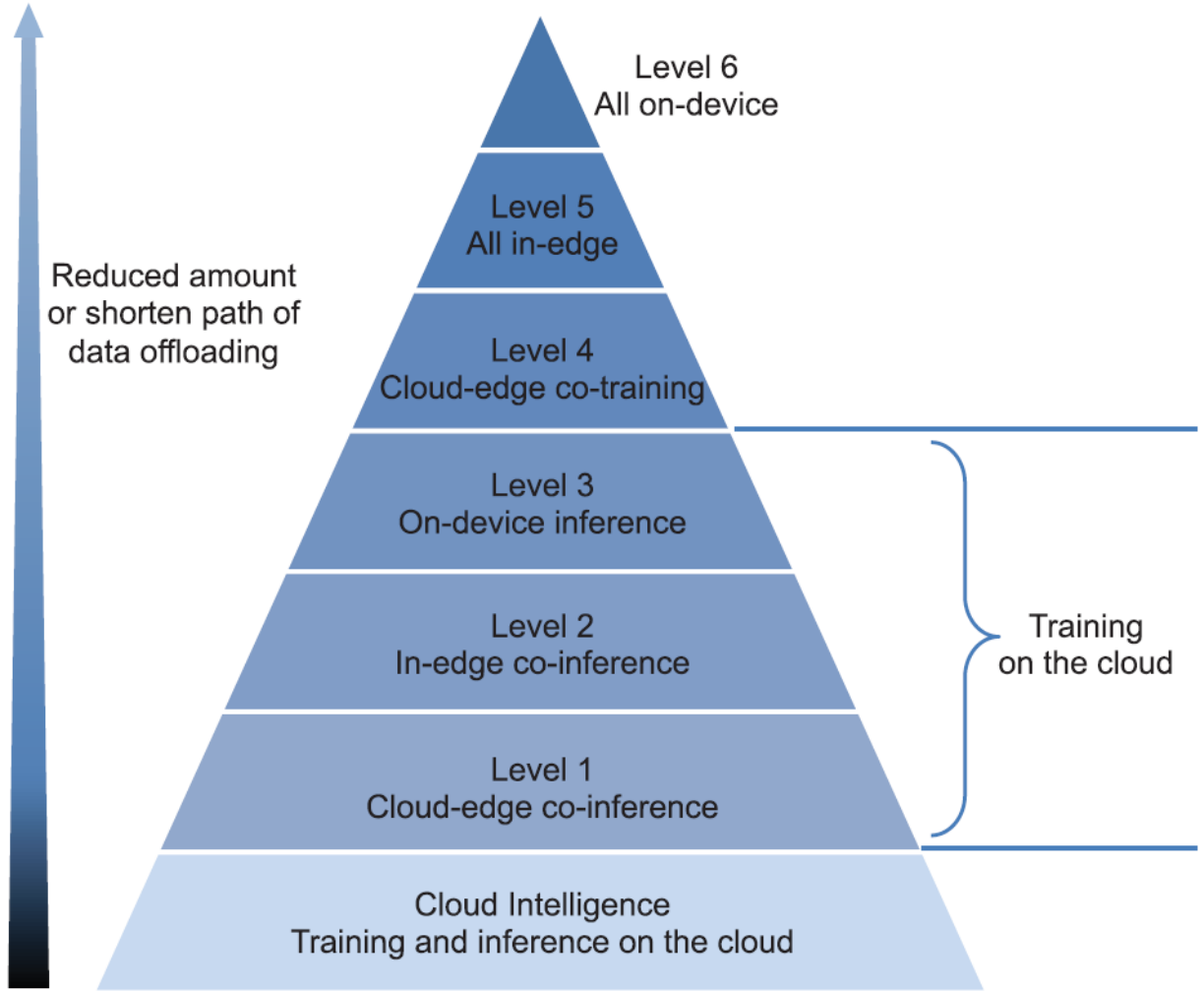
Source: https://github.com/CeLuigi/models-comparison.pytorch

Cloud vs. Edge vs. Tiny AI



Source: ABI Research: TinyML

Six-level ratings of Edge Intelligence



Source: Edge Intelligence: Paving the Last Mile of Artificial Intelligence With Edge Computing (Zhou et al. 2019)

Why AI at the Edge?

Bandwidth

1 billion+ cameras worldwide
10’s of petabytes per day

Latency

Safety-critical services
Realtime decisions

Privacy

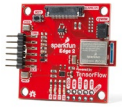
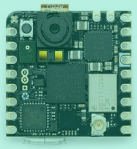
Data Redaction + Confidentiality
Private cloud or on-premises storage

Connectivity

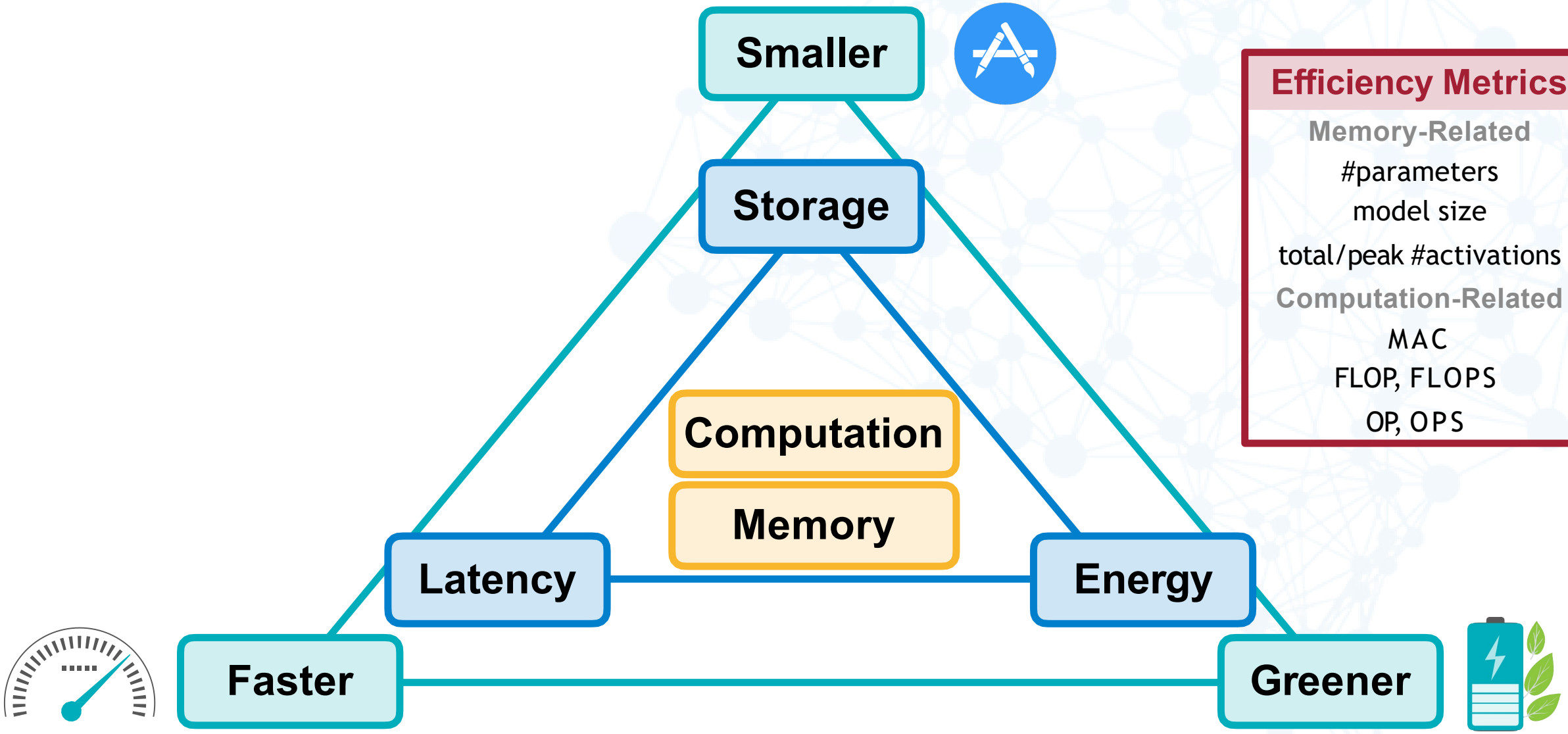
50% of populated world < 8mbps
Bulk of uninhabited world no 3G+

Source: [1]

Embedded Platforms

	Board	MCU / ASIC	Clock	Memory	Sensors	Radio
	Himax WE-I Plus EVB	HX6537-A 32-bit EM9D DSP	400 MHz	2MB flash 2MB RAM	Accelerometer, Mic, Camera	None
	Arduino Nano 33 BLE Sense	32-bit nRF52840	64 MHz	1MB flash 256kB RAM	Mic, IMU, Temp, Humidity, Gesture, Pressure, Proximity, Brightness, Color	BLE
	SparkFun Edge 2	32-bit ArtemisV1	48 MHz	1MB flash 384kB RAM	Accelerometer, Mic, Camera	BLE
	Espressif EYE	32-bit ESP32-D0WD	240 MHz	4MB flash 520kB RAM	Mic, Camera	WiFi, BLE
	Arduino Nicla Vision	Dual Arm® Cortex® M7/M4	240 MHz 480 MHz	2MB Flash 1MB RAM	6-Axis IMU 2 MP Color Camera Distance / Time Of Flight sensor Microphone	WiFI, BLE

Efficiency of Neural Networks



Efficiency Metrics

Memory-Related

#parameters

model size

total/peak #activations

Computation-Related

MAC

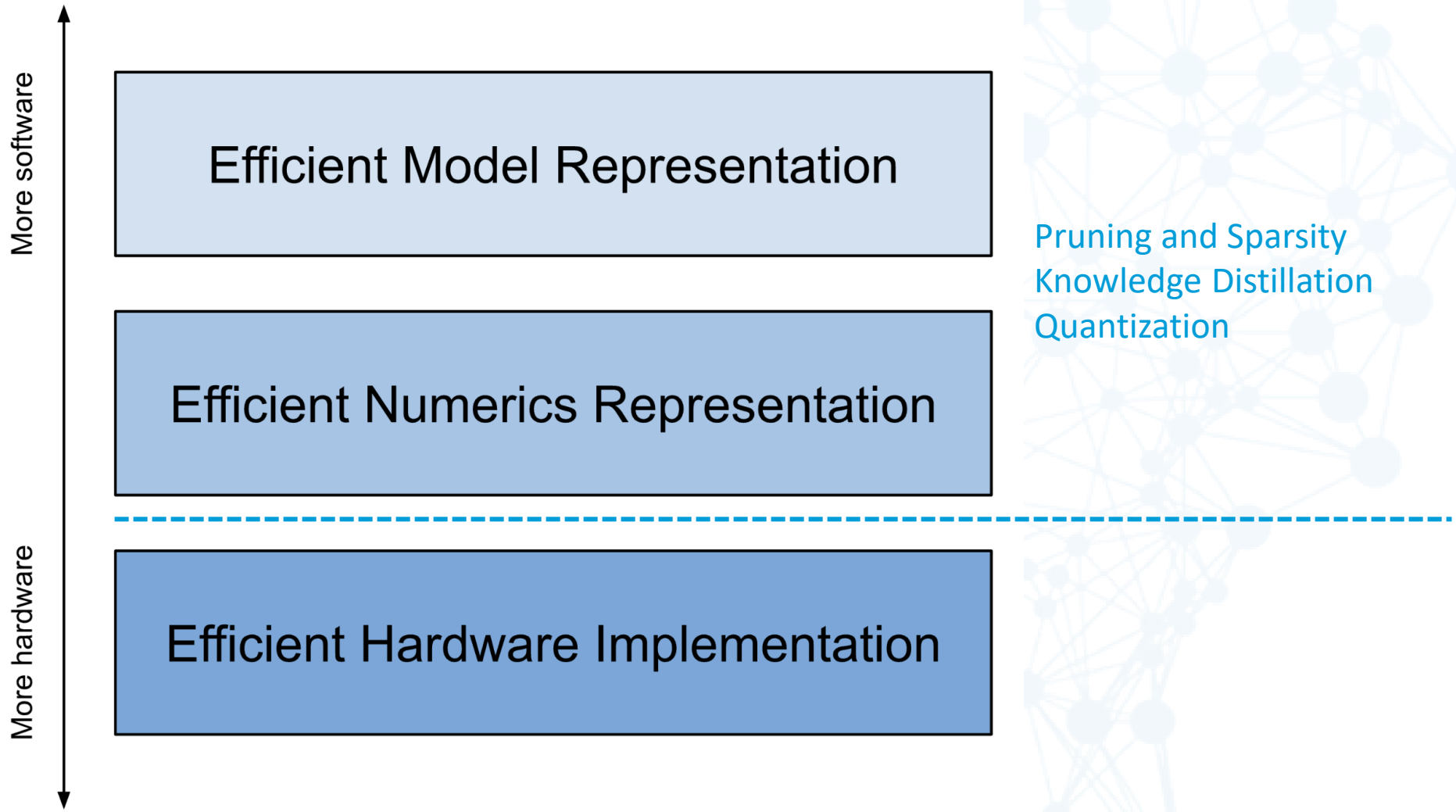
FLOP, FLOPS

OP, OPS

Source: [7]

Image source: 1

Efficient AI models



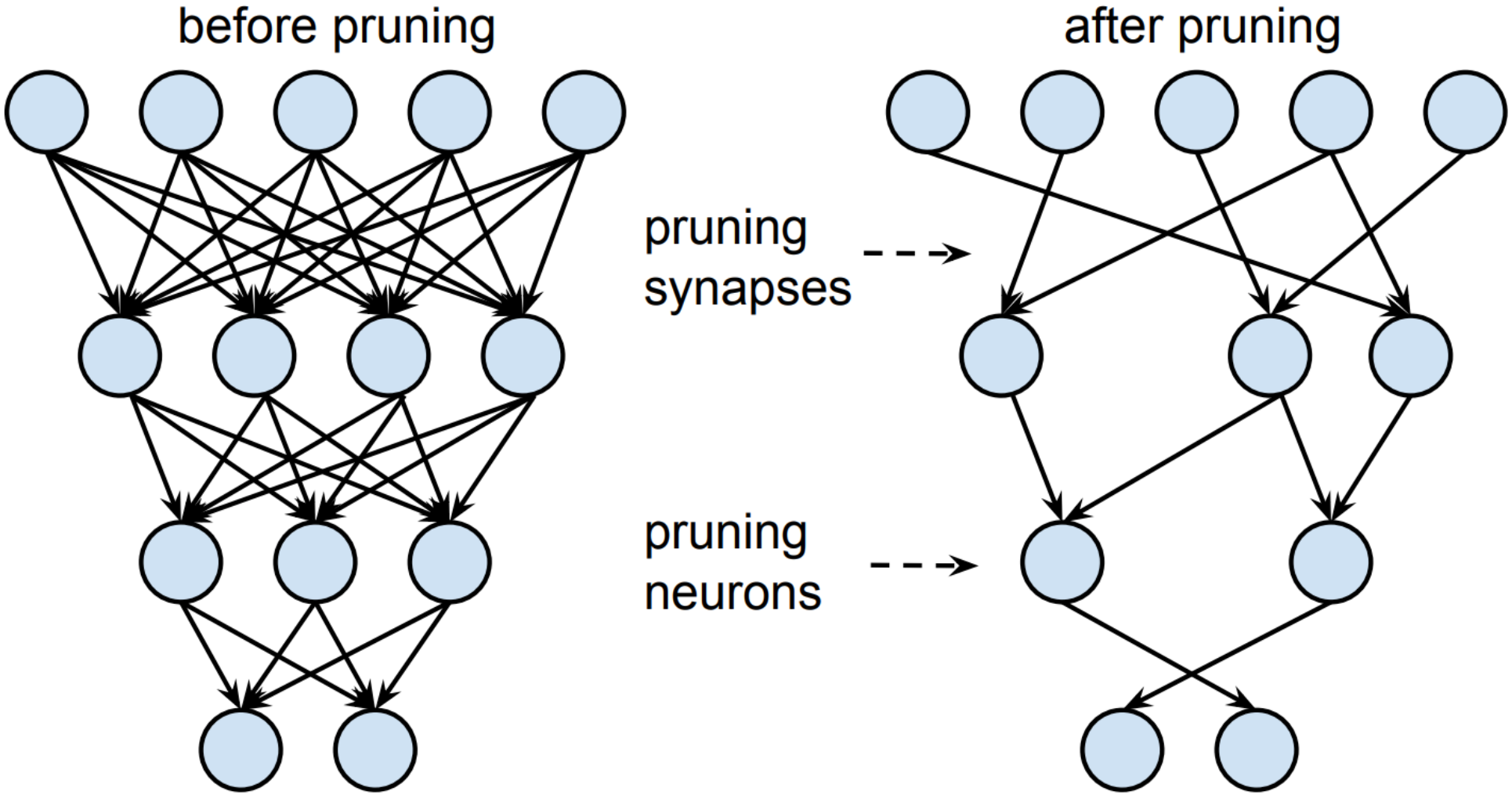
Source: [2]

Efficient AI models

Make AI models run faster and efficiently on low-power hardware

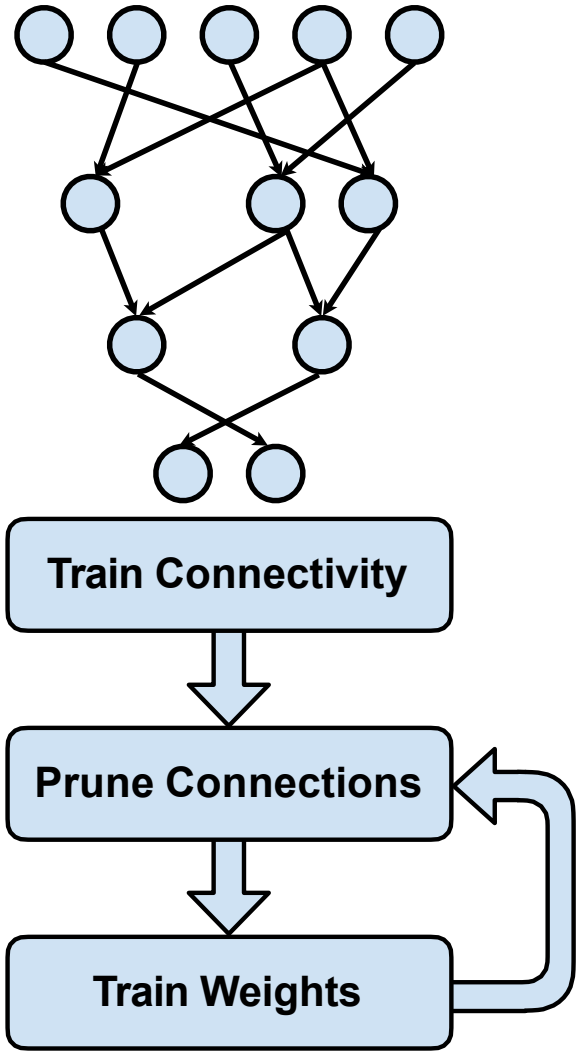
Source: [4]

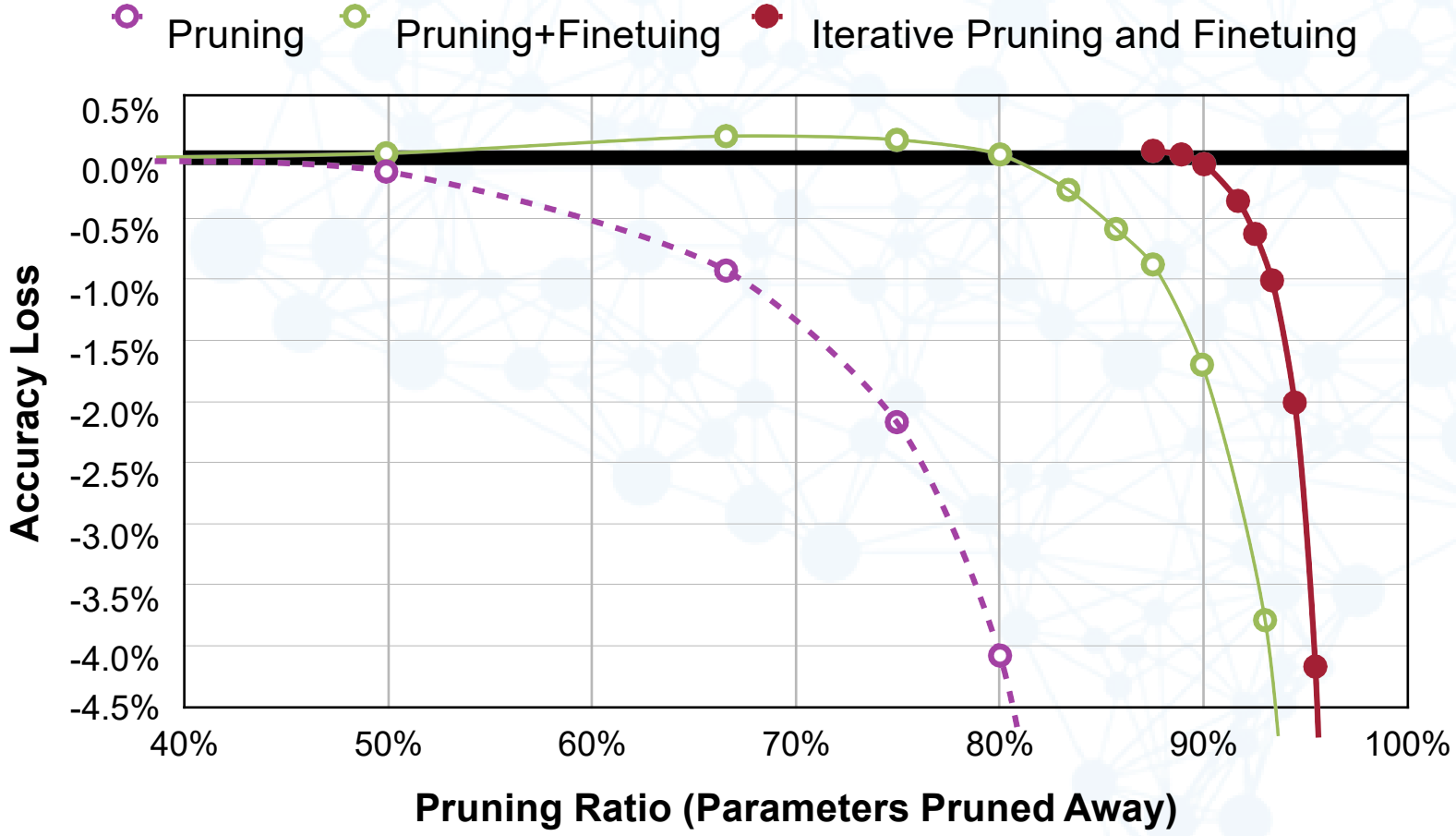
Pruning in Neural Networks



Source: Learning both Weights and Connections for Efficient Neural Networks (Han et al. 2015)

Pruning in Neural Networks





Source: Learning both Weights and Connections for Efficient Neural Networks (Han et al. 2015)

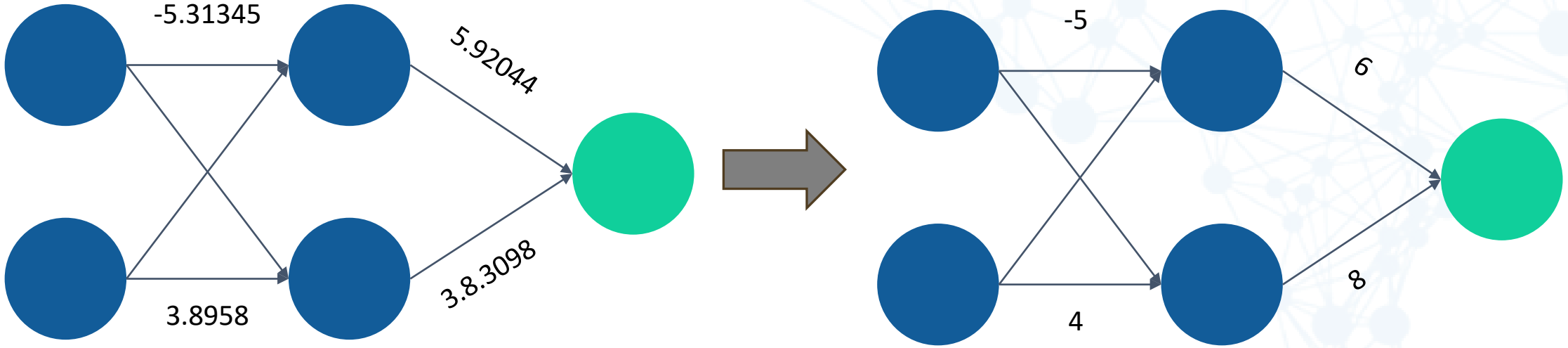
Pruning in Neural Networks

Neural Network	#Parameters			MACs
	Before Pruning	After Pruning	Reduction	Reduction
AlexNet	61 M	6.7 M	**9** ×	3 ×
VGG-16	138 M	10.3 M	**12** ×	5 ×
GoogleNet	7 M	2.0 M	**3.5** ×	5 ×
ResNet50	26 M	7.47 M	**3.4** ×	6.3 ×
SqueezeNet	1 M	0.38 M	**3.2** ×	3.5 ×

Source: Efficient Methods and Hardware for Deep Learning (Han 2017)

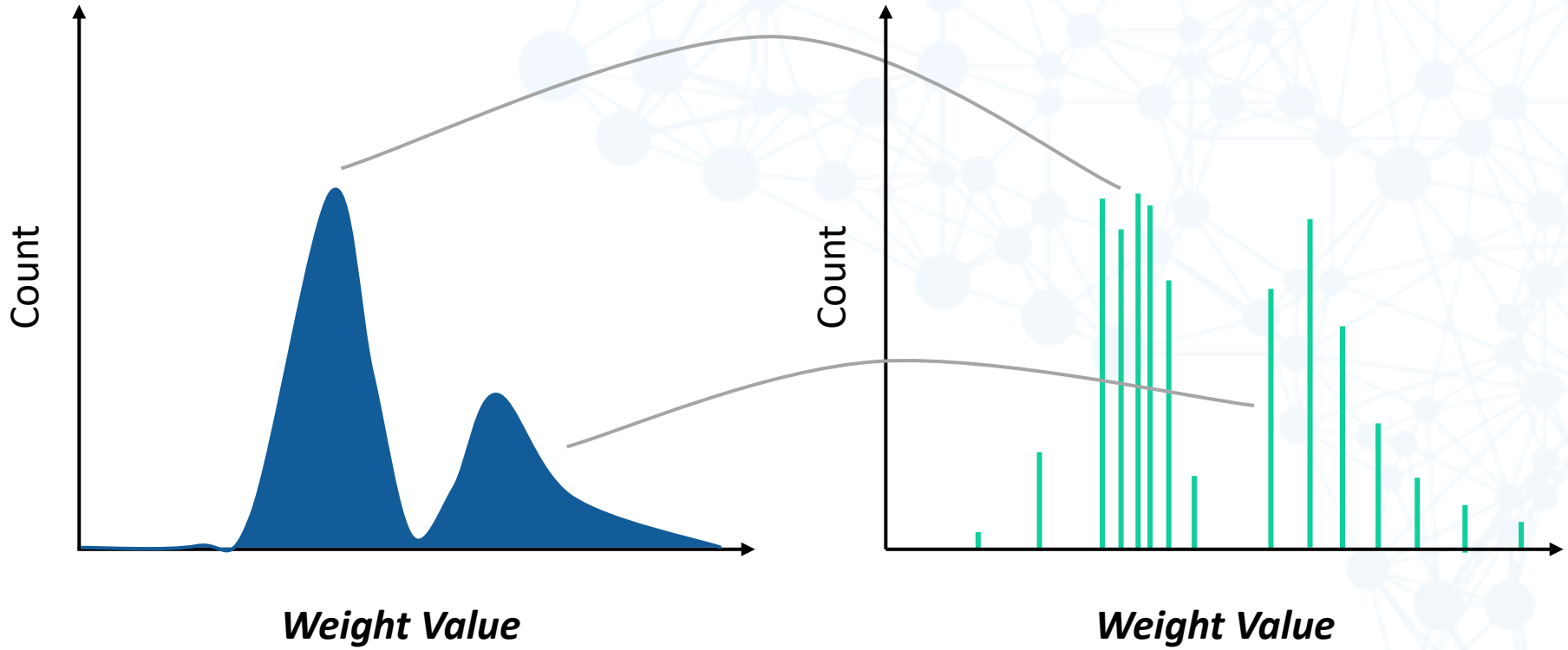
Quantization

Quantization is an optimization that works by **reducing the precision** of the numbers used to represent a model's parameters, which by default are 32-bit floating point numbers. This results in a **smaller model size, better portability** and **faster computation**.



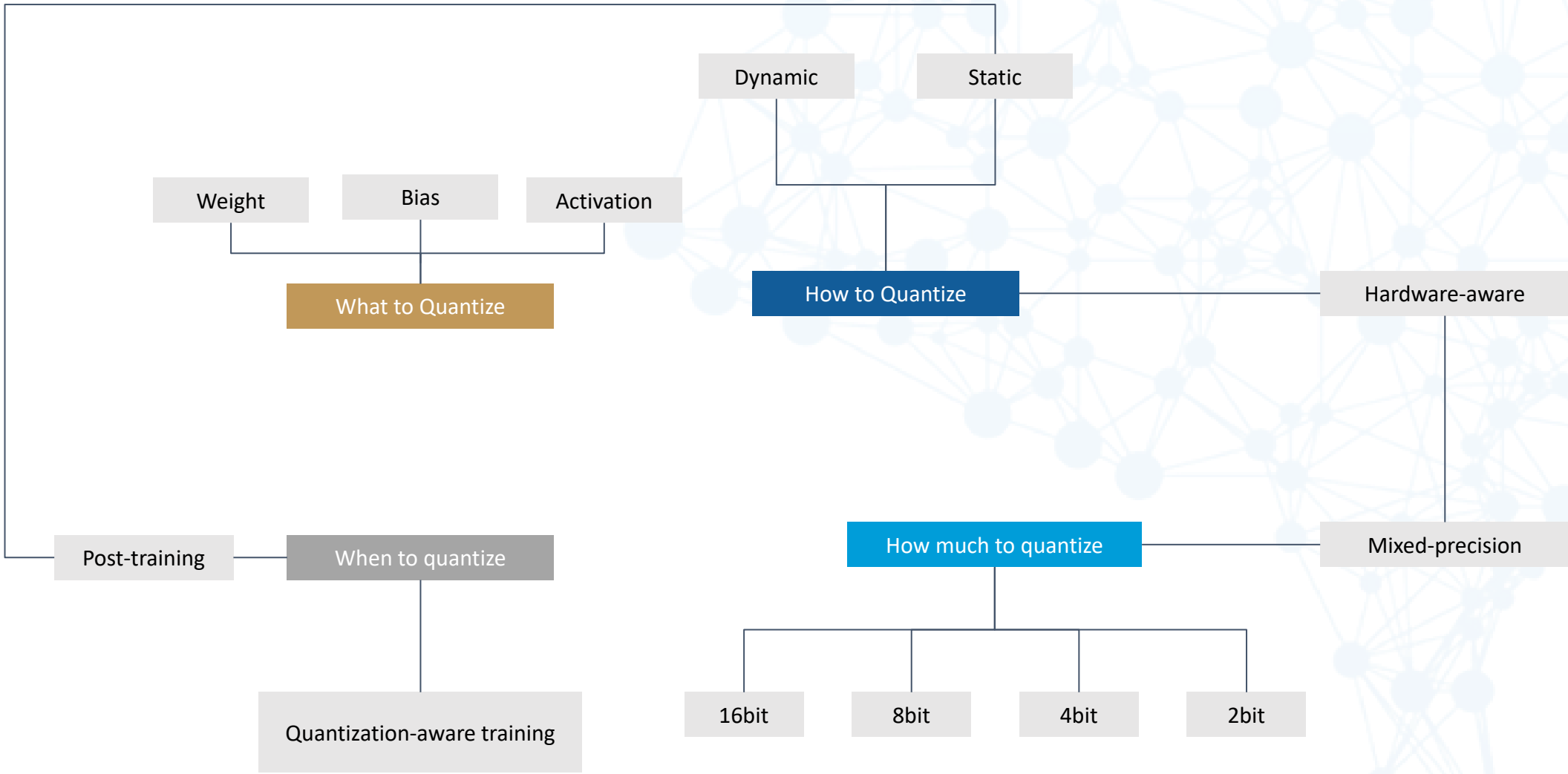
Source: [4]

Reduce Precision (Discretize)



Source: [4]

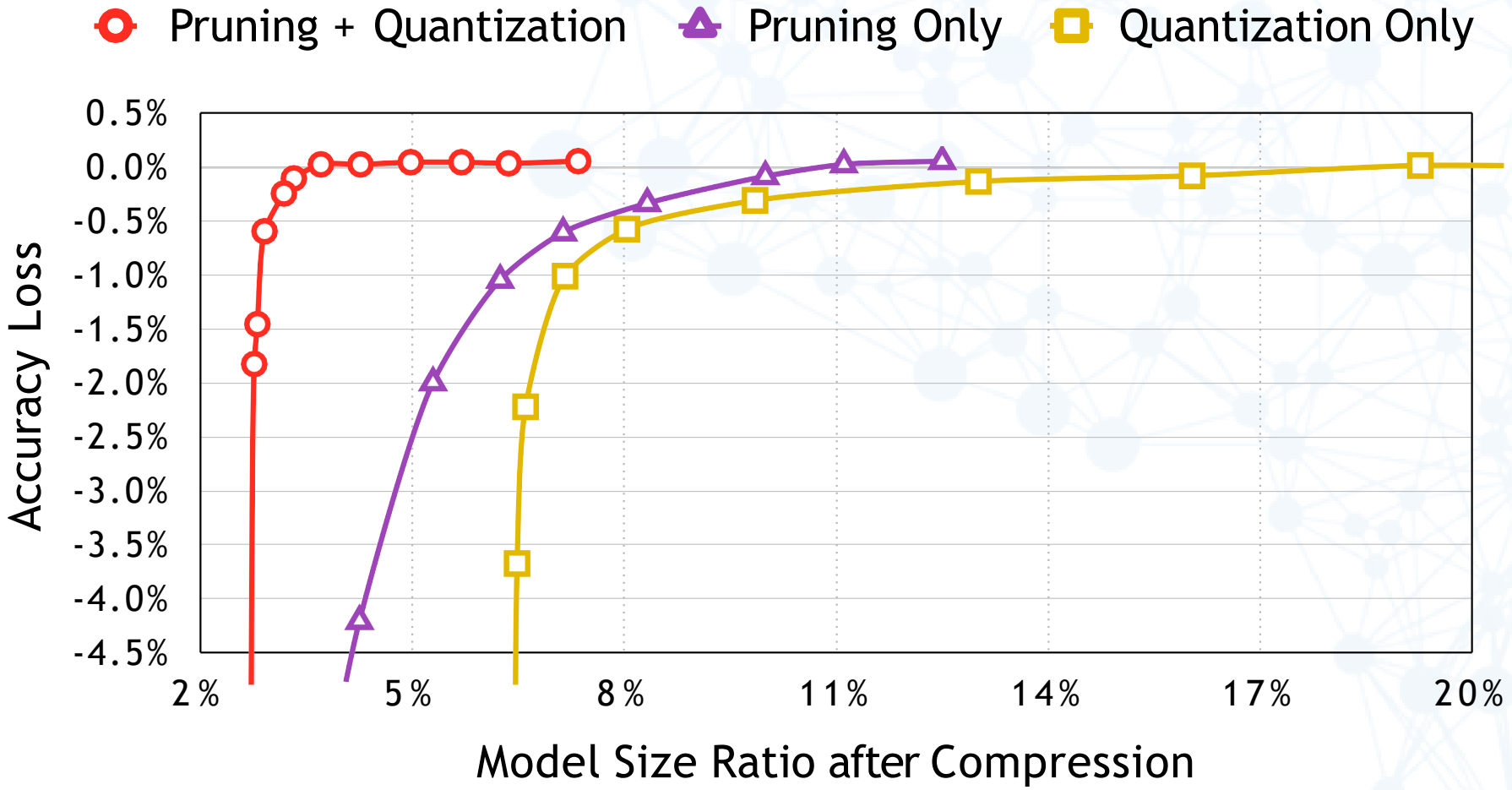
Quantization



Source: [4]

Clustering-based Weight Quantization

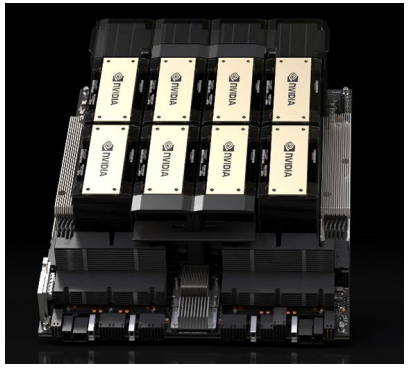
Accuracy vs. compression rate for AlexNet on ImageNet dataset

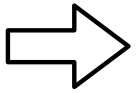


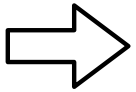
Source: Deep Compression (Han et al., ICLR 2016)

On-Device Training is Challenging

Memory size is too small to hold DNNs





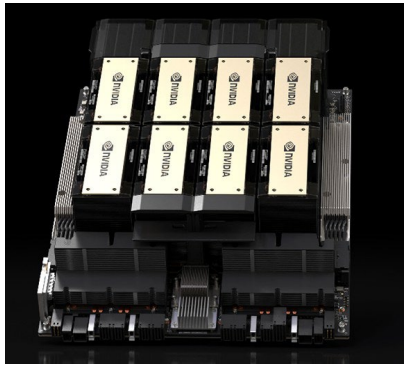


	Cloud AI	Mobile AI	Tiny AI
Memory (Activation)	141GB	4GB	320kB
Storage (Weights)	~TB/PB	256GB	1MB

Source: [7]

On-Device Training is Challenging

Memory size is too small to hold DNNs



	Cloud AI	Mobile AI	Tiny AI
Memory (Activation)	141GB	4GB	320kB
Storage (Weights)	~TB/PB	256GB	1MB

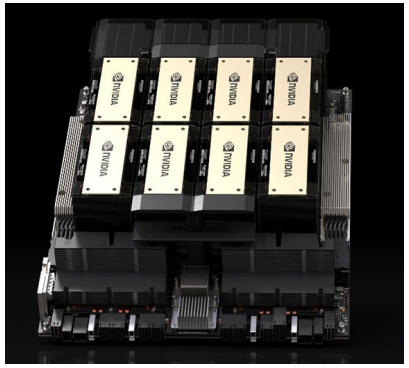
13,000x smaller

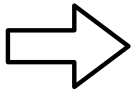
1,000,000x smaller

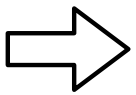
Source: [7]

On-Device Training is Challenging

Memory size is too small to hold DNNs





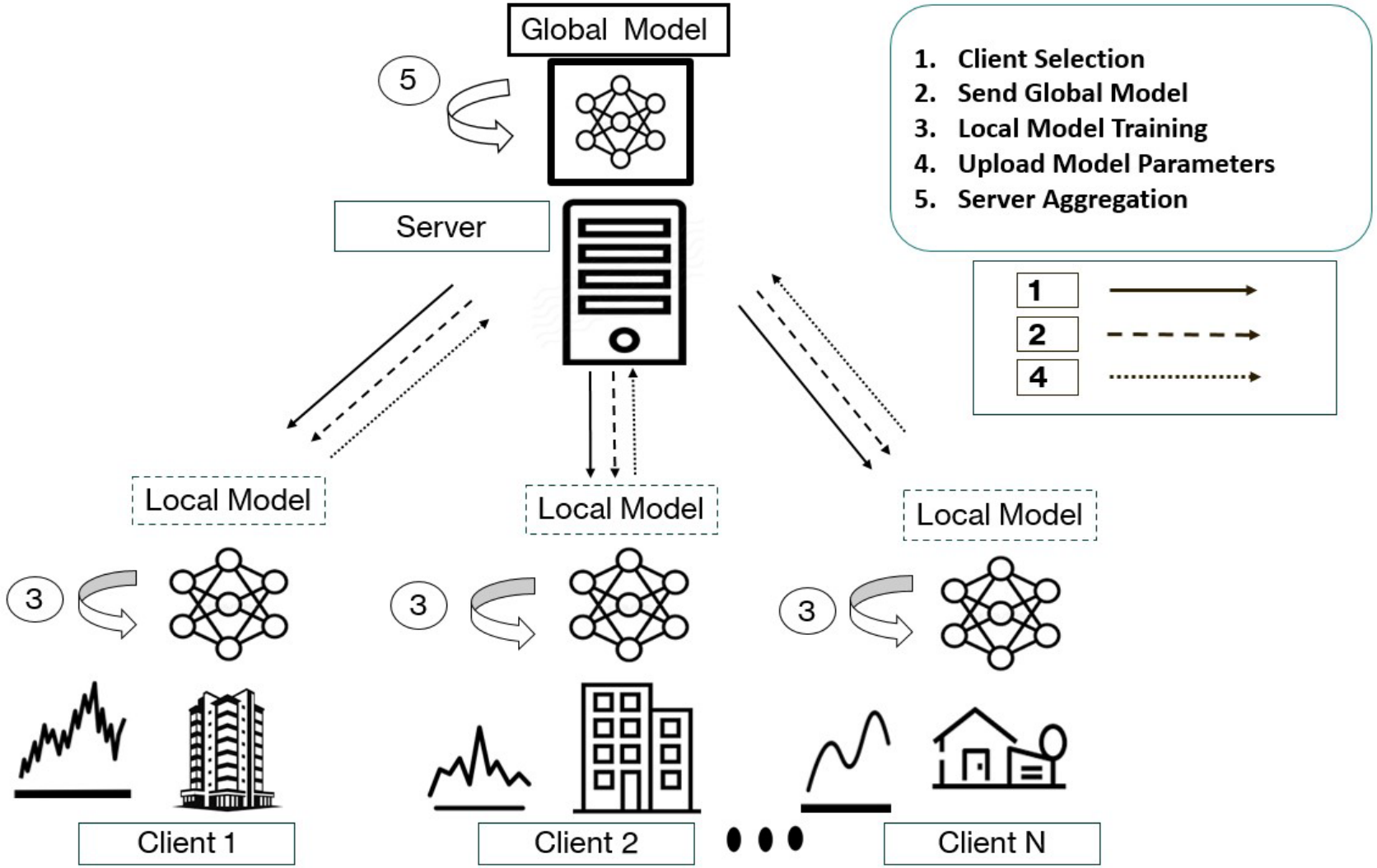


	Cloud AI	Mobile AI	Tiny AI
Memory (Activation)	141GB	4GB	320kB
Storage (Weights)	~TB/PB	256GB	1MB

- We need to reduce both **weights** and **activation** to fit DNNs for On-Device Training

Source: [7]

Federated Learning



Google AI Edge

Deploy AI across mobile, web, and embedded applications

On device

Reduce latency. Work offline. Keep your data local & private.

Cross-platform

Run the same model across Android, iOS, web, and embedded.

Multi-framework

Compatible with JAX, Keras, PyTorch, and TensorFlow models.

Full AI edge stack

Flexible frameworks, turnkey solutions, hardware accelerators

Google’s LiteRT

LiteRT (short for Lite Runtime), formerly known as TensorFlow Lite, is Google's high-performance runtime for on-device AI. You can find ready-to-run LiteRT models for a wide range of ML/AI tasks, or convert and run TensorFlow, PyTorch, and JAX models to the TFLite format using the AI Edge conversion and optimization tools.

Key features

- **Optimized for on-device machine learning**: LiteRT addresses five key ODML constraints: latency (there's no round-trip to a server), privacy (no personal data leaves the device), connectivity (internet connectivity is not required), size (reduced model and binary size) and power consumption (efficient inference and a lack of network connections).
- **Multi-platform support**: Compatible with Android and iOS devices, embedded Linux, and microcontrollers.
- **Multi-framework model options**: AI Edge provides tools to convert models from TensorFlow, PyTorch, and JAX models into the FlatBuffers format (`.tflite`), enabling you to use a wide range of state-of-the-art models on LiteRT. You also have access to model optimization tools that can handle quantization and metadata.
- **Diverse language support**: Includes SDKs for Java/Kotlin, Swift, Objective-C, C++, and Python.
- **High performance**: Hardware acceleration through specialized delegates like GPU and iOS Core ML.

Source: https://ai.google.dev/edge/litert

TensorFlow Model Optimization Toolkit

The *TensorFlow Model Optimization Toolkit* is a suite of tools for optimizing ML models for deployment and execution. Among many uses, the toolkit supports techniques used to:

- Reduce latency and inference cost for cloud and edge devices (e.g. mobile, IoT).
- Deploy models to edge devices with restrictions on processing, memory, power-consumption, network usage, and model storage space.
- Enable execution on and optimize for existing hardware or new special purpose accelerators.

Choose the model and optimization tool depending on your task:

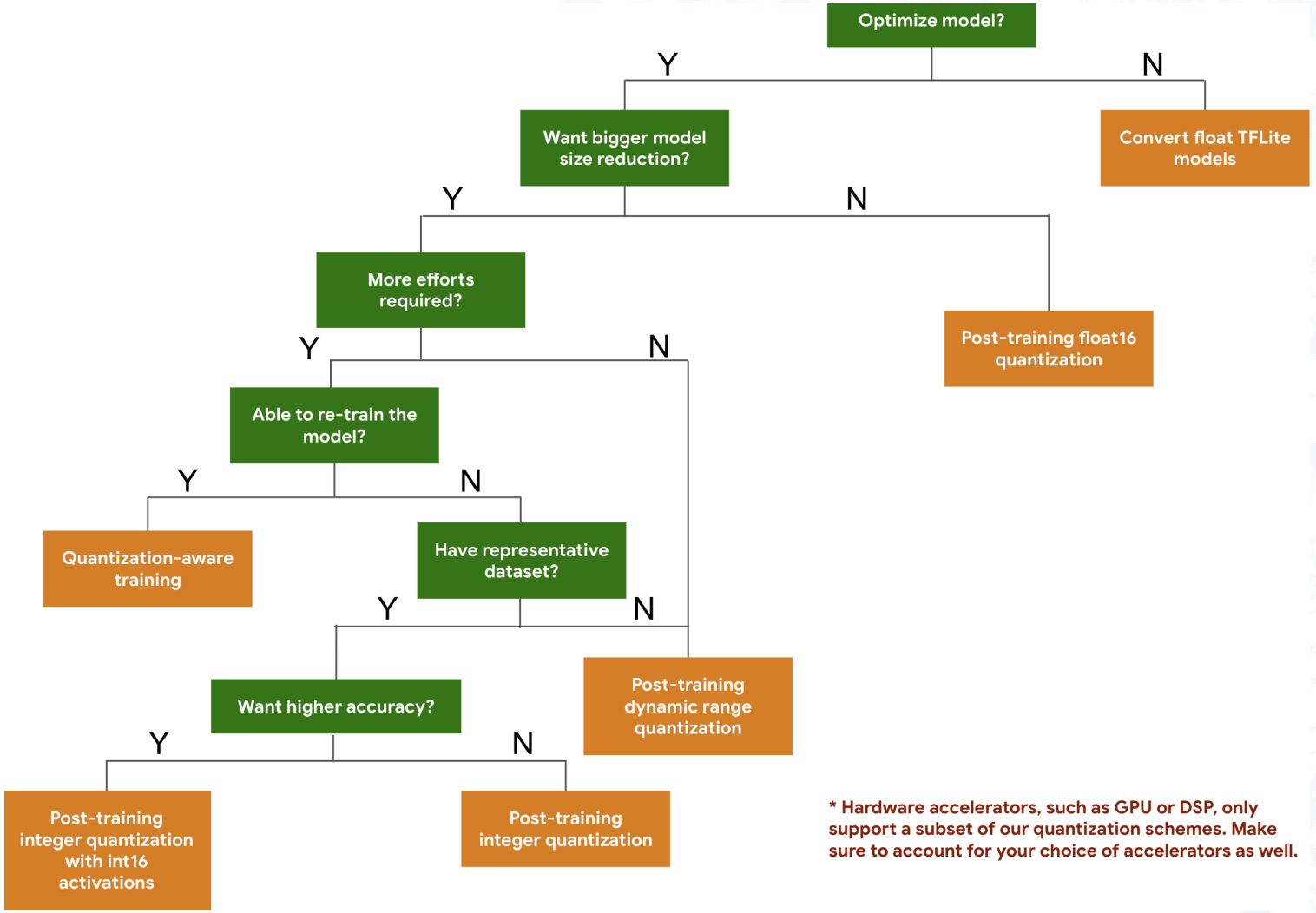
Improve performance with off-the-shelf models

In many cases, pre-optimized models can improve the efficiency of your application.

```
import tensorflow as tf
import tensorflow_model_optimization as tfmot
import tf_keras as keras

model = keras.Sequential([...])

pruning_schedule = tfmot.sparsity.keras.PolynomialDecay(
                      initial_sparsity=0.0, final_sparsity=0
                      begin_step=2000, end_step=4000)

model_for_pruning = tfmot.sparsity.keras.prune_low_magnitude
    model, pruning_schedule=pruning_schedule)
...

model_for_pruning.fit(...)
```

Source: https://www.tensorflow.org/model_optimization

TensorFlow Model Optimization Toolkit



* Hardware accelerators, such as GPU or DSP, only support a subset of our quantization schemes. Make sure to account for your choice of accelerators as well.

Source: https://ai.google.dev/edge/litert/models/model_optimization

TensorFlow Model Optimization Toolkit

Quantized models are 4x smaller and 1.4x faster!

Model	Top-1 Accuracy (Original)	Top-1 Accuracy (Post Training Quantized)	Top-1 Accuracy (Quantization Aware Training)	Latency (Original) (ms)	Latency (Post Training Quantized) (ms)	Latency (Quantization Aware Training) (ms)	Size (Original) (MB)	Size (Optimized) (MB)
Mobilenet-v1-1-224	0.709	0.657	0.70	124	112	64	16.9	4.3
Mobilenet-v2-1-224	0.719	0.637	0.709	89	98	54	14	3.6
Inception_v3	0.78	0.772	0.775	1130	845	543	95.7	23.9
Resnet_v2_101	0.770	0.768	N/A	3973	2868	N/A	178.3	44.9

Source: https://ai.google.dev/edge/litert/models/model_optimization

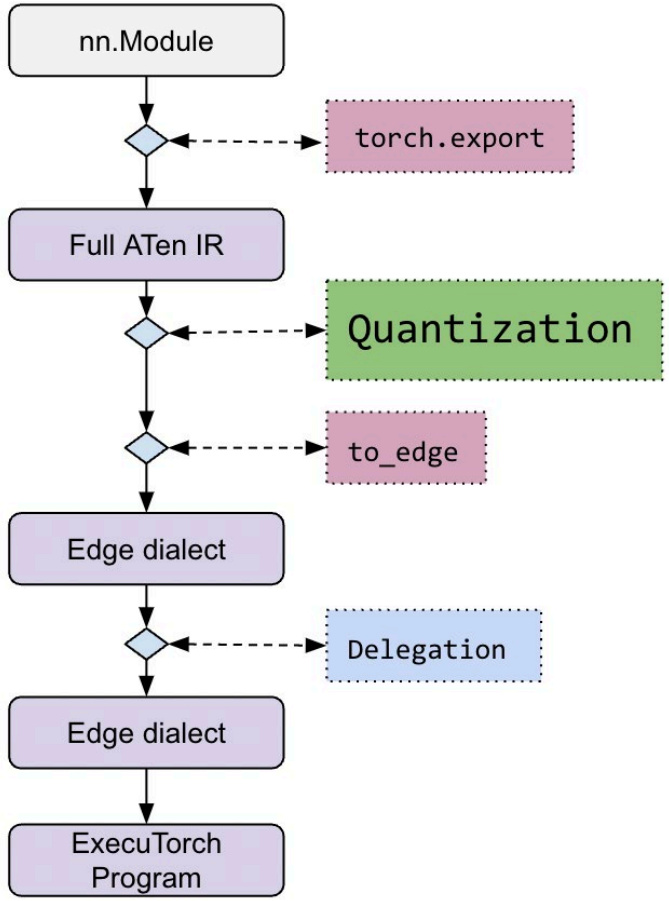
PyTorch Edge

ExecuTorch: A powerful on-device AI Framework

CONTRIBUTORS 219 | STARS 2.6K | DISCORD JOIN US | DOCUMENTATION

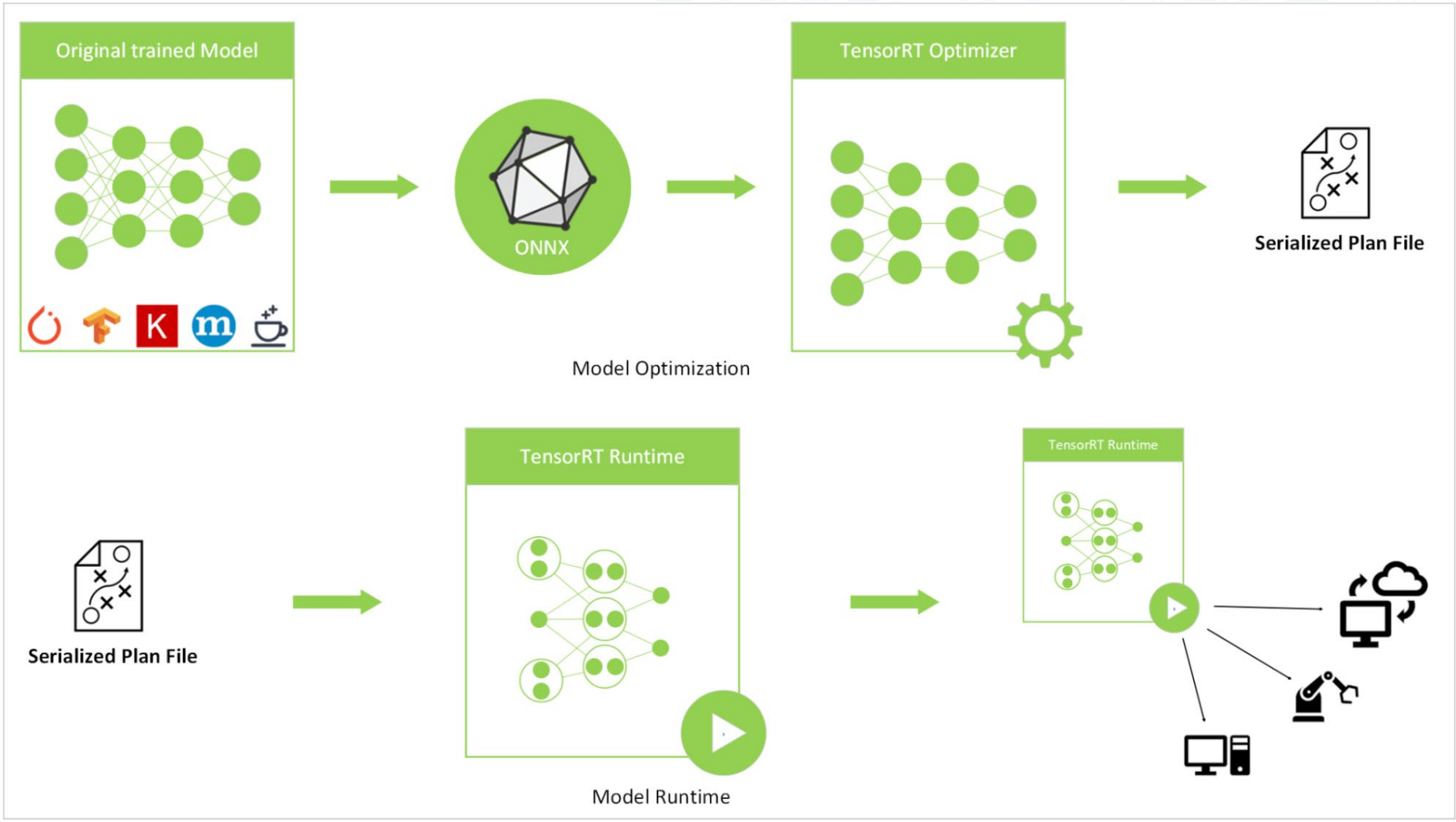
ExecuTorch is an end-to-end solution for on-device inference and training. It powers much of Meta's on-device AI experiences across Facebook, Instagram, Meta Quest, Ray-Ban Meta Smart Glasses, WhatsApp, and more.

It supports a wide range of models including LLMs (Large Language Models), CV (Computer Vision), ASR (Automatic Speech Recognition), and TTS (Text to Speech).



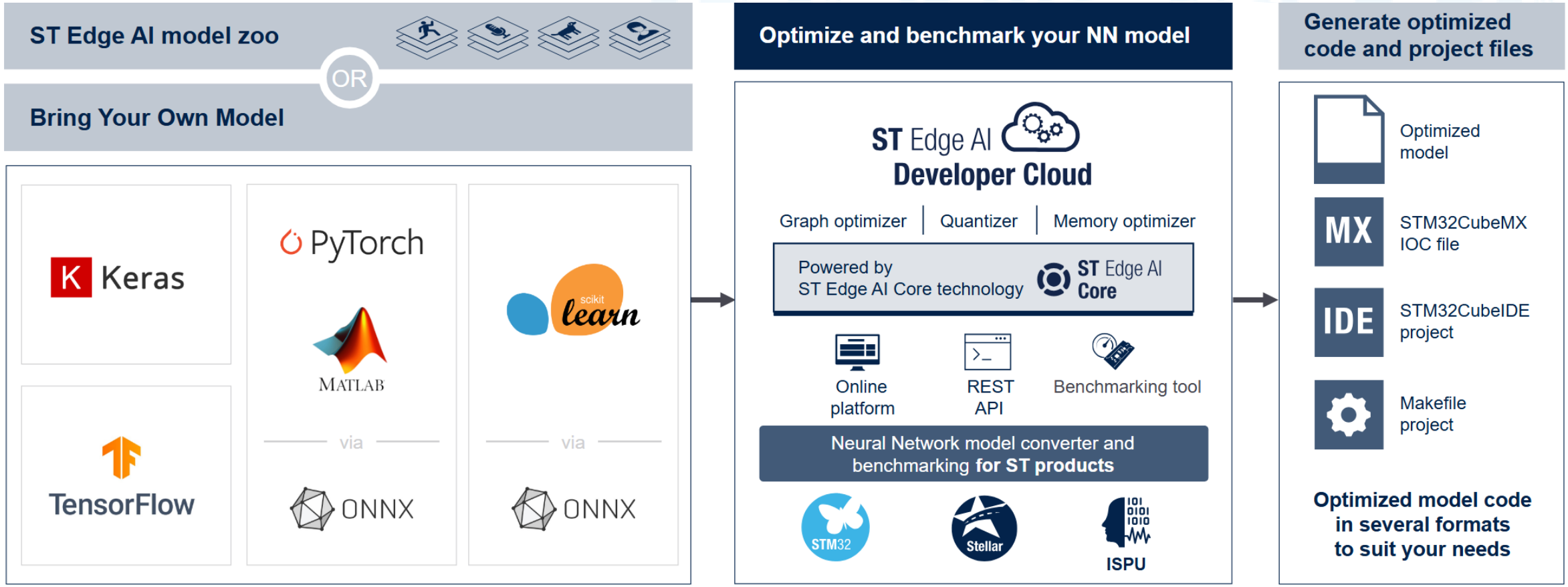
Source: https://pytorch.org/executorch-overview

NVIDIA TensorRT Model Optimizer



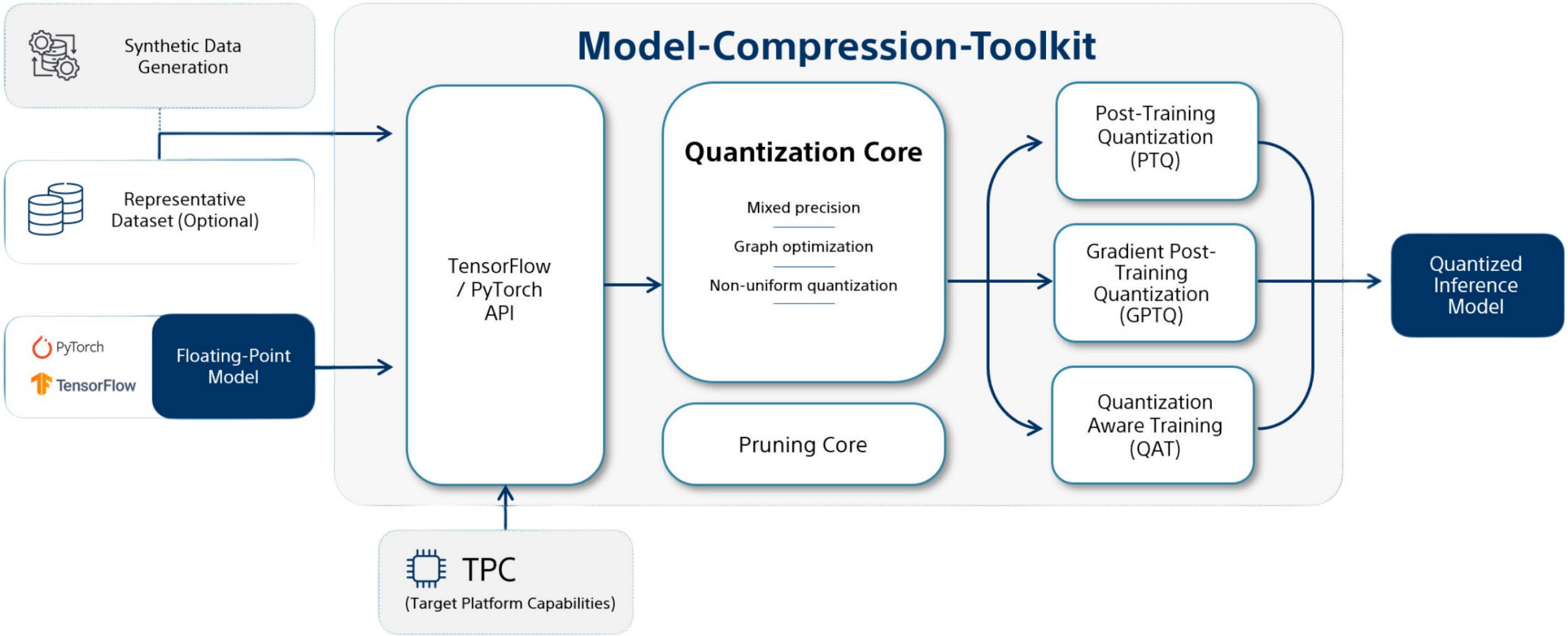
Source: https://developer.nvidia.com/tensorrt https://github.com/NVIDIA/TensorRT-Model-Optimizer

STMicroelectronics's Edge AI Platform



Source: https://stm32ai-cs.st.com/home

SONY's Model Compression Toolkit (MCT)



Source: https://github.com/sony/model_optimization

Intel OpenVINO

1 | Model

2 | Optimize

3 | Deploy

PyTorch

TensorFlow

TensorFlow Lite

PaddlePaddle

ONNX

Keras

Industry Model Zoos

Use open source models from industry model zoos such as Hugging Face, TensorFlow, Keras, PyTorch, PaddlePaddle, and ONNXpretrained models.

Optimum* for Intel

Use OpenVINO™ toolkit as an extension in Hugging Face* transformer models and gain model compression and performance benefits.

intel GETi

Build computer vision models in a fraction of the time and with less data.

Model Converter for OpenVINO™

Convert a trained model from supported frameworks.

IR Data

Read, load, infer

OpenVINO format (intermediate representation file, .pb, .tflite, .onnx)

Direct Model Conversion for TensorFlow* and PyTorch*

An option to skip steps to get to deployment faster.

Model Compression with NNCF

Neural Network Compression Framework (NNCF) provides quantization aware-training, model pruning, and sparsity along with posttraining optimization.

Jupyter* Notebook

Get sample code on the latest models to help get your application into production faster.

OpenVINO Model Server

Serve models over gRPC, REST, or C API endpoints.

OpenVINO Runtime

Common Python*, C, and C++ APIs that abstract low-level programming for each of the following devices.

Source: https://docs.openvino.ai/2025/index.html

Intel OpenVINO

Neural Network Compression Framework (NNCF)

Key Features • Installation • Documentation • Usage • Tutorials and Samples • Third-party integration • Model Zoo

release v2.15.0 | website docs | license Apache 2.0 | downloads 3M

python 3.9+ | backends openvino | pytorch | onnx | tensorflow | OS Linux | Windows | MacOS

Neural Network Compression Framework (NNCF) provides a suite of post-training and training-time algorithms for optimizing inference of neural networks in OpenVINO™ with a minimal accuracy drop.

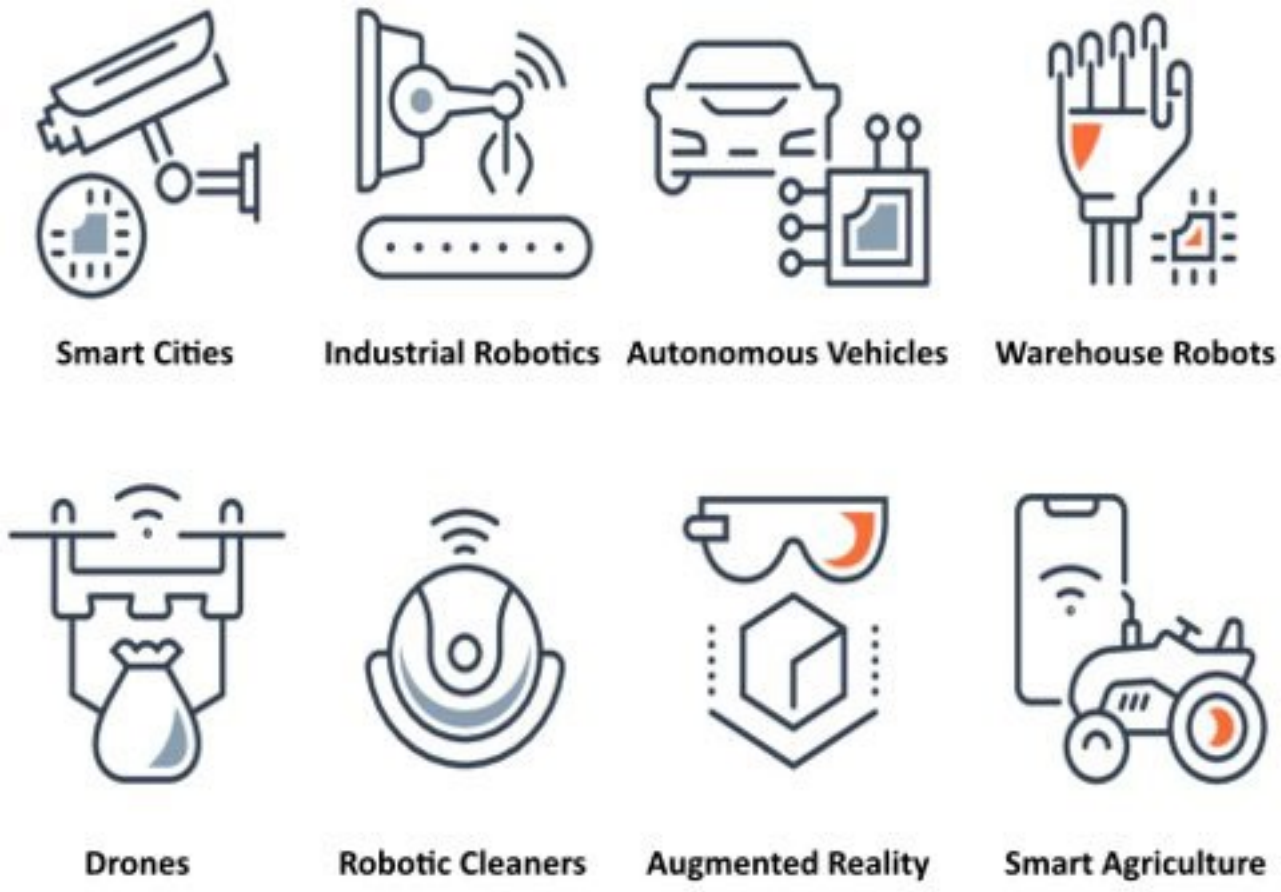
NNCF is designed to work with models from PyTorch, TorchFX, TensorFlow, ONNX and OpenVINO™.

NNCF provides samples that demonstrate the usage of compression algorithms for different use cases and models. See compression results achievable with the NNCF-powered samples on the NNCF Model Zoo page.

The framework is organized as a Python* package that can be built and used in a standalone mode. The framework architecture is unified to make it easy to add different compression algorithms for both PyTorch and TensorFlow deep learning frameworks.

Source: https://github.com/openvinotoolkit/nncf

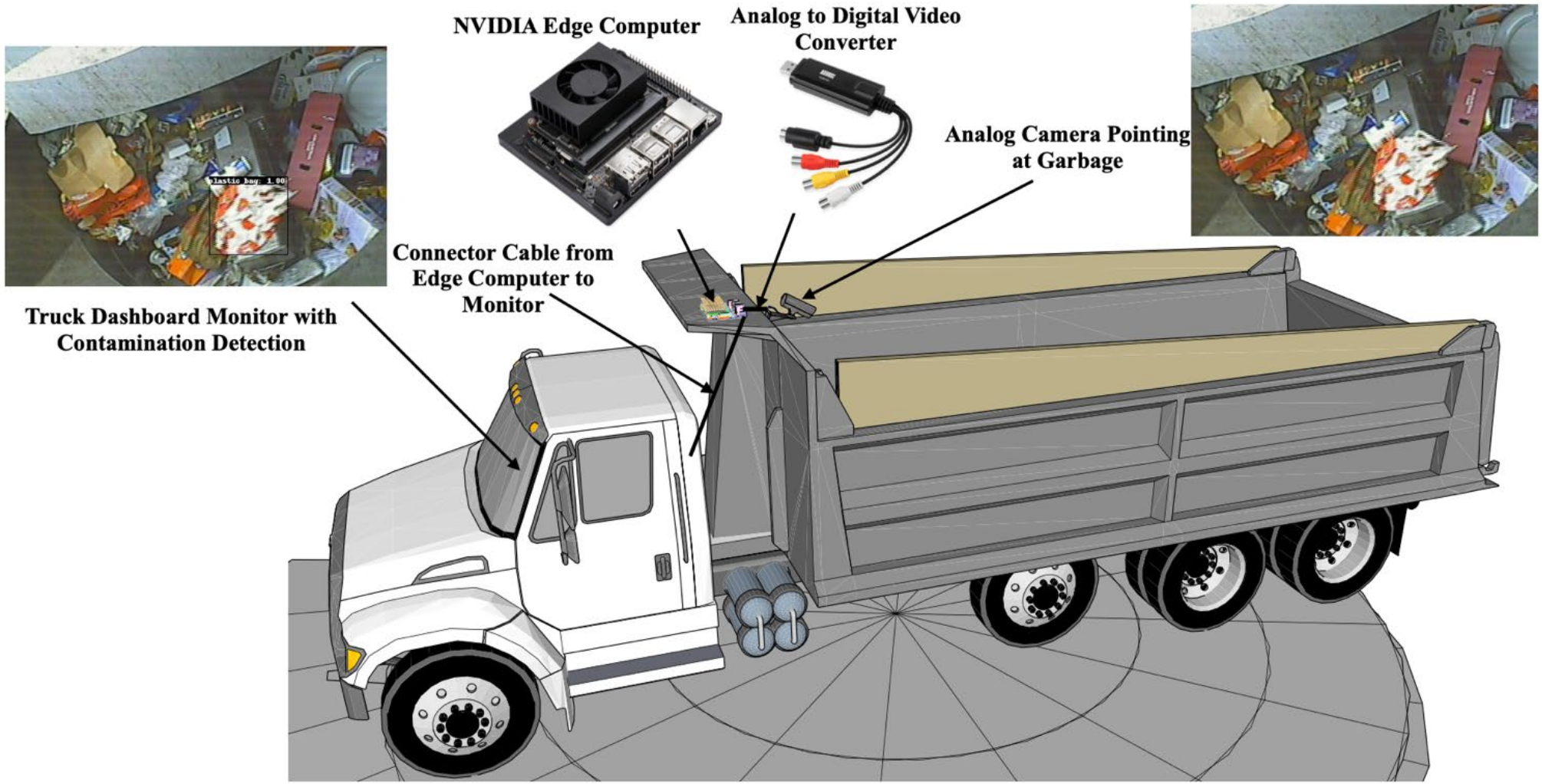
Edge AI applications



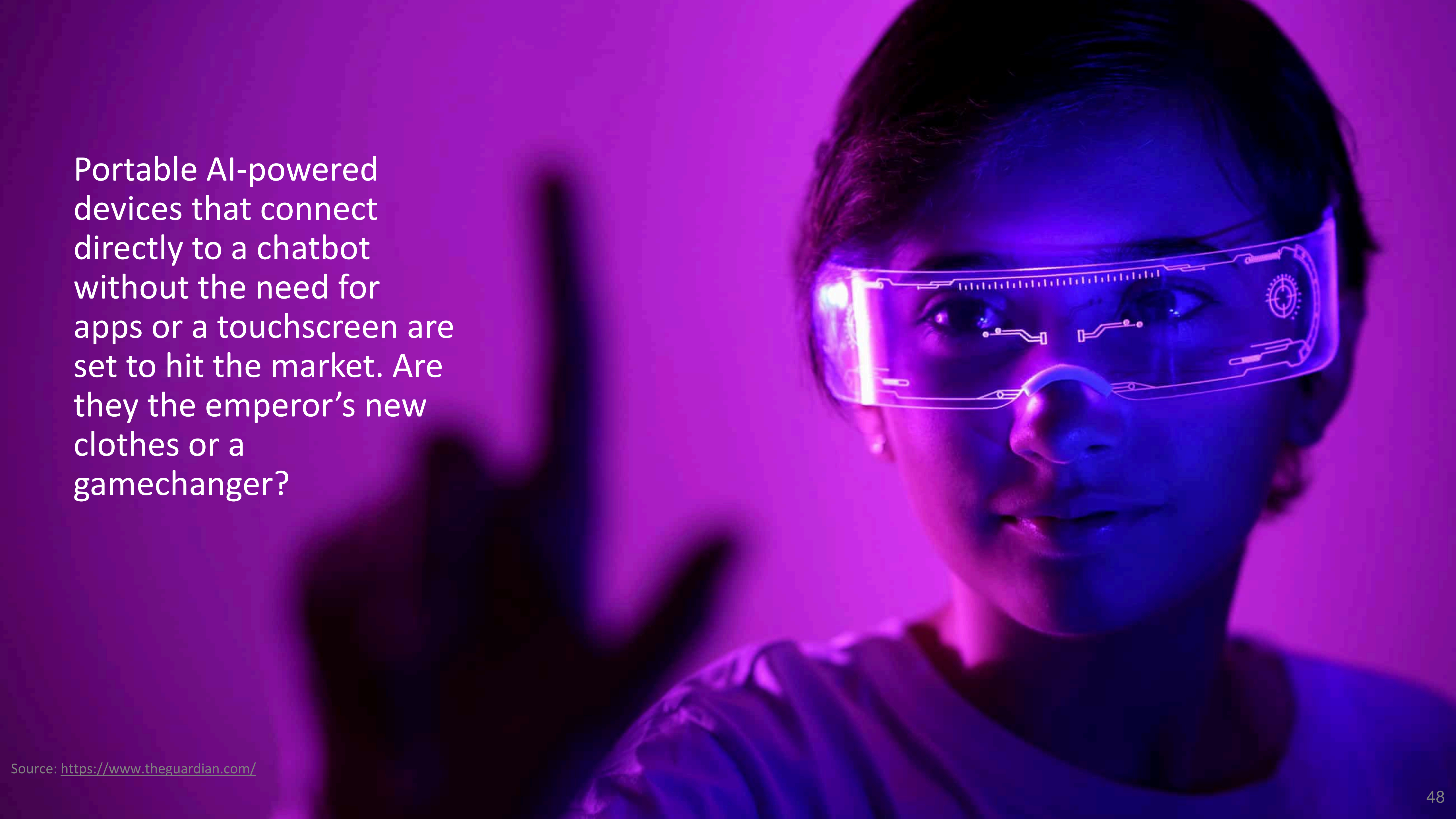
Source: Internet

Source: Internet

Detecting Real-Time Waste Contamination Using Edge Computing and Video Analytics



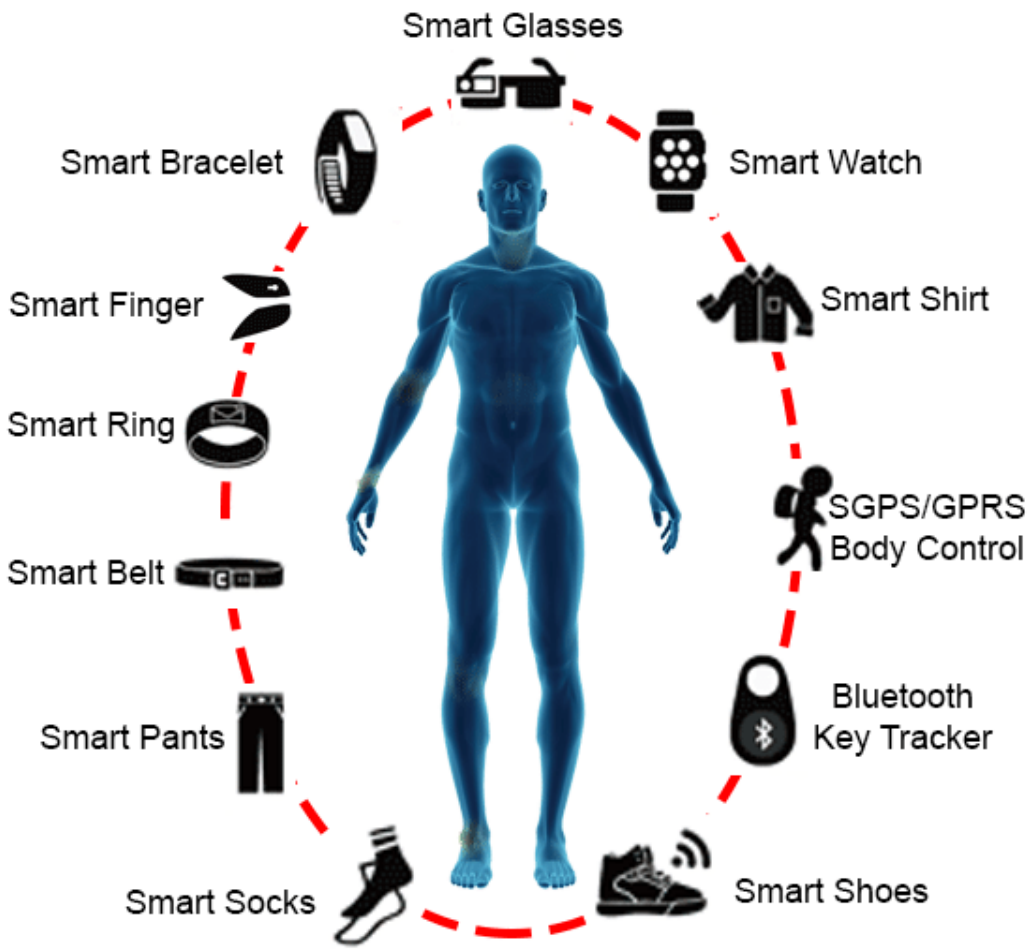
Source: https://developer.nvidia.com/blog/detecting-real-time-waste-contamination-using-edge-computing-and-video-analytics/



Portable AI-powered devices that connect directly to a chatbot without the need for apps or a touchscreen are set to hit the market. Are they the emperor's new clothes or a gamechanger?

Source: https://www.theguardian.com/

Wearable AI



Source: Internet

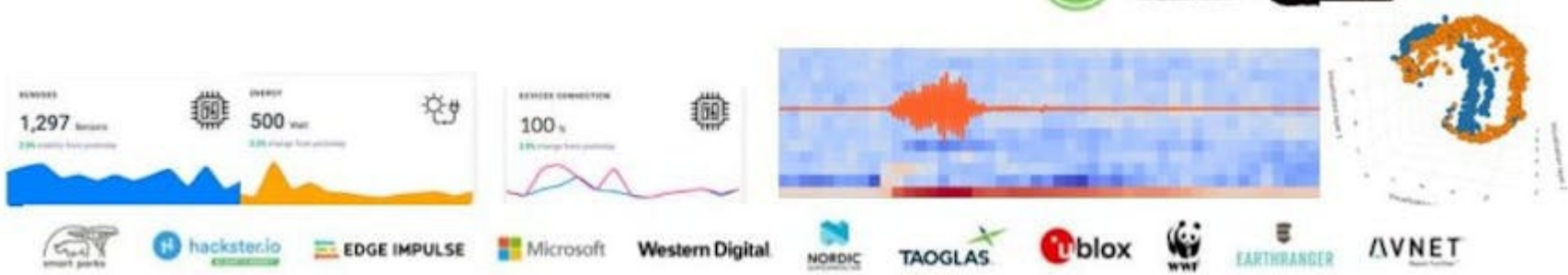
Healthcare AI

StethoMe® AI detects abnormal sounds in the respiratory system!!!

Source: https://www.stethome.com/

EleTect – EDGE IMPULSE

and /IOTCONNECT based Smart Wildlife Tracker Technology

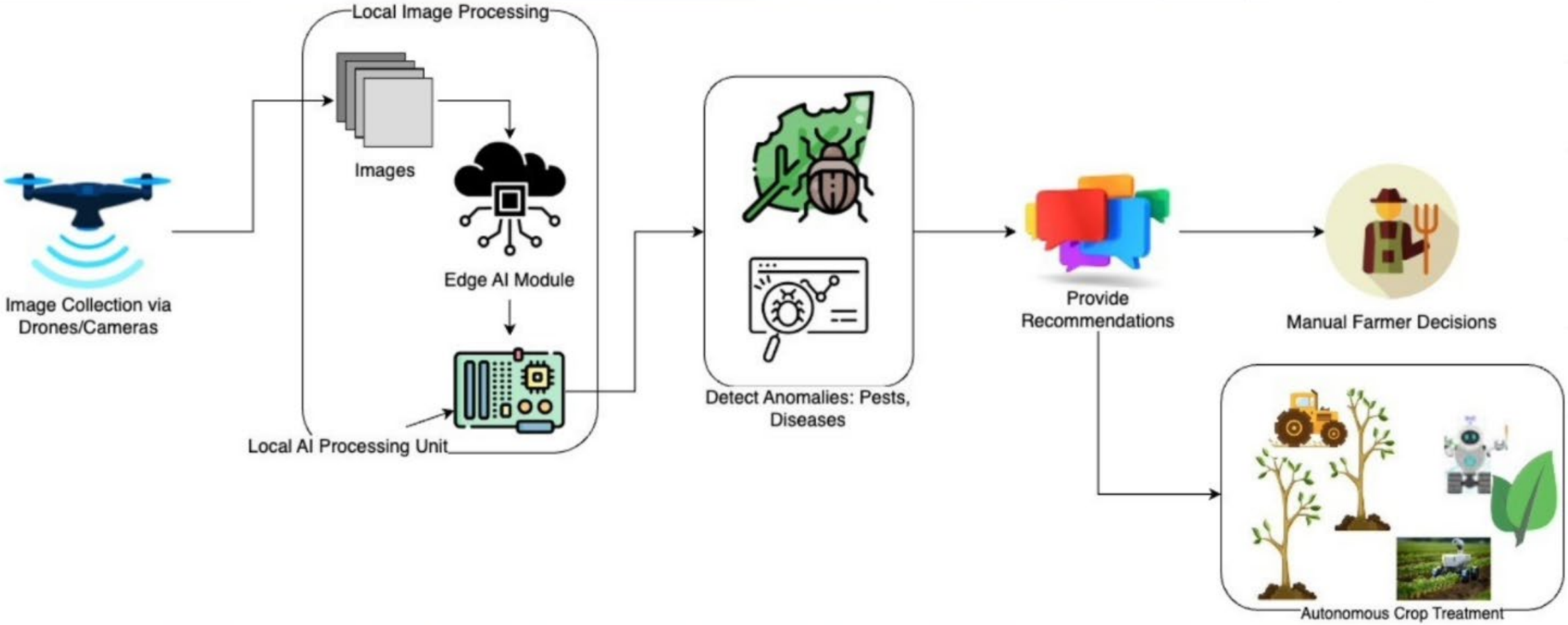


Source: https://www.hackster.io/dhruvsheth_/eletect-tinyml-and-iot-based-smart-wildlife-tracker-c03e5a

Smart Farming

Source: https://www.libramli.ai/

Smart Farming



Source: https://www.xenonstack.com/blog/edge-ai-agriculture

AI Camera

Edge-analytics powered
No dependence on server

On-premise solution
No need to pull live video over poor network

Source: https://www.honeywellbuildings.in

Edge AI Based Object & Face Detection Cameras VM-72B5AIVE

VMukti's smart product family, 4k products are equipped with Edge AI features such as Facial Recognition, Object Detection, Intrusion Detection and more. VMukti FHD, H.265+ PTZ Dome & Bullet Camera delivers up to FHD resolution (2592×1944, effectively four times that of Full HD) at 30 frames per second (fps), providing users with ultra-high-definition video viewing experience.

Source: https://www.vmukti.com/products/object-detection-camera/

What is an AI PC?

AI PCs use artificial intelligence technologies to elevate productivity, creativity, gaming, entertainment, security, and more. They have a CPU, GPU, and NPU to handle AI tasks locally and more efficiently.
-Intel

Source: https://www.scmp.com/ and https://www.intel.com/

What is an AI PC?

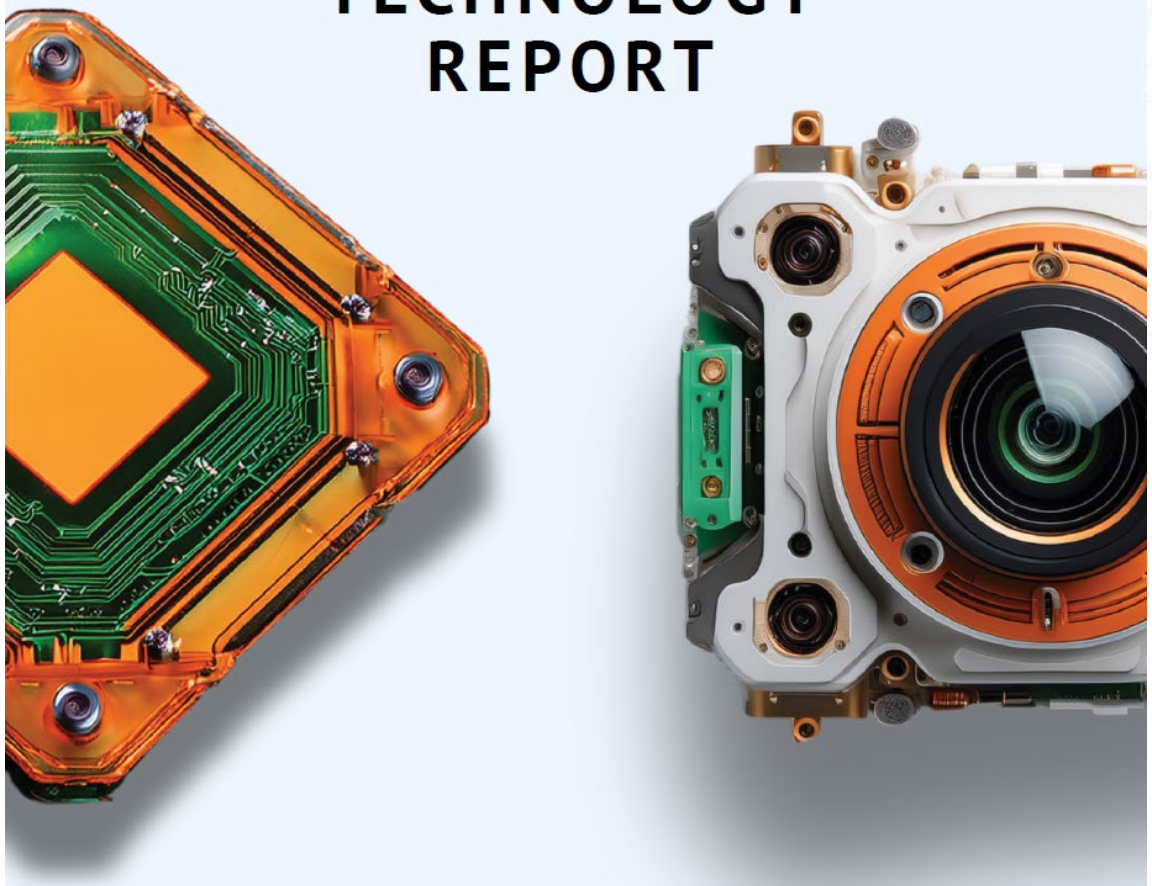
An "AI-PC" is a PC with **new NPU silicon** that brings new AI experiences in productivity, creativity, and security through a combination of the CPU, GPU, and the new NPU.

Source: https://robquickenden.blog/2024/03/what-is-an-ai-pc/

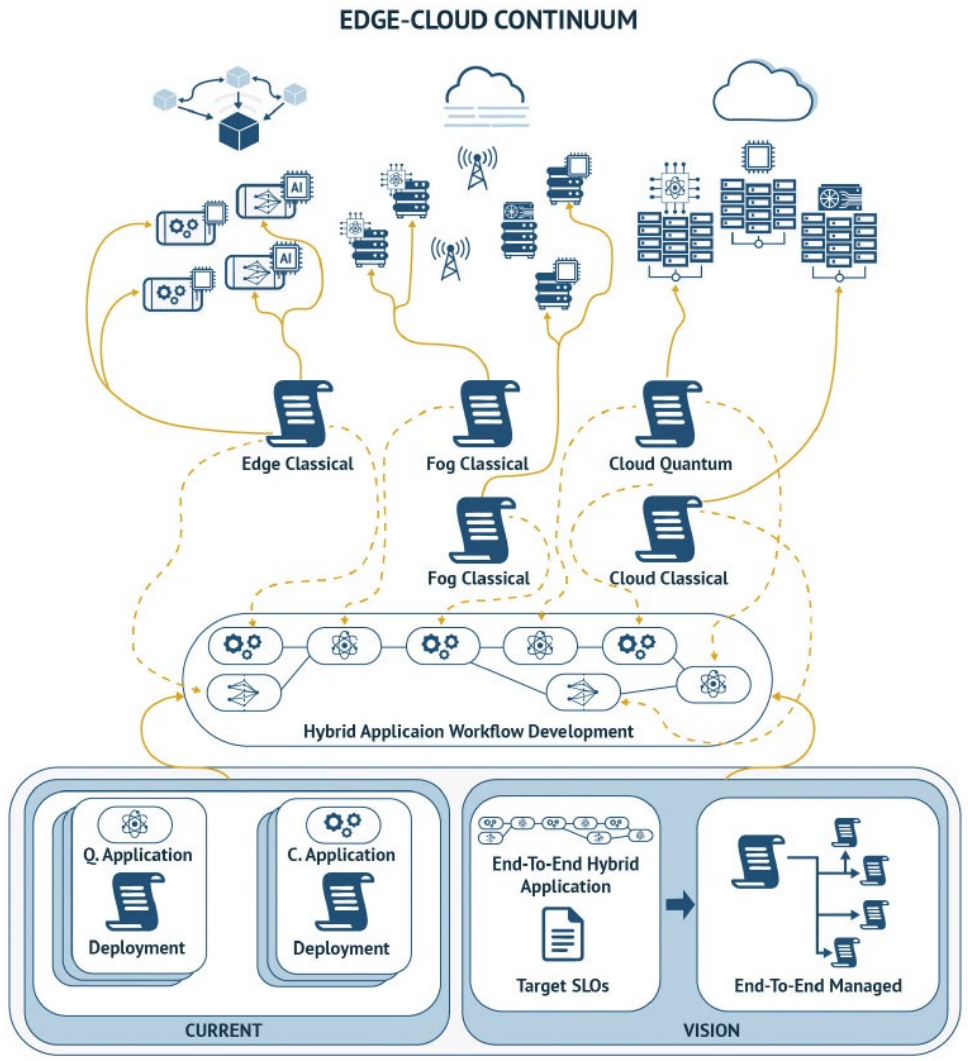
WEVOLVER

EDGEAI FOUNDATION

THE 2025 EDGE AI TECHNOLOGY REPORT



The guide to understanding the current state of the art in hardware & software for Edge AI.

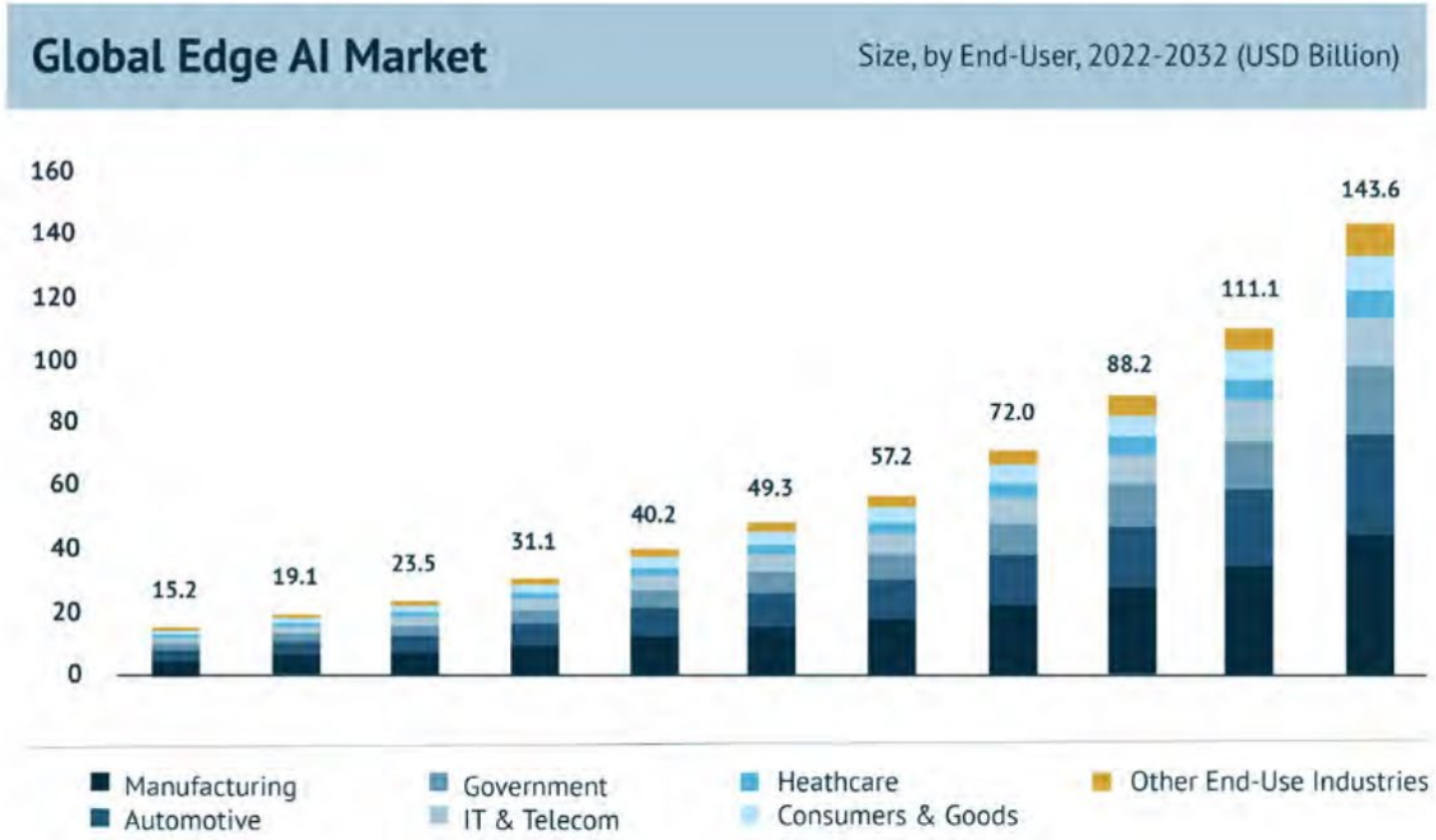


A Distributed Classical-Quantum Hybrid Platform (Image Credit: A. Furutanpey et al.)[xix]

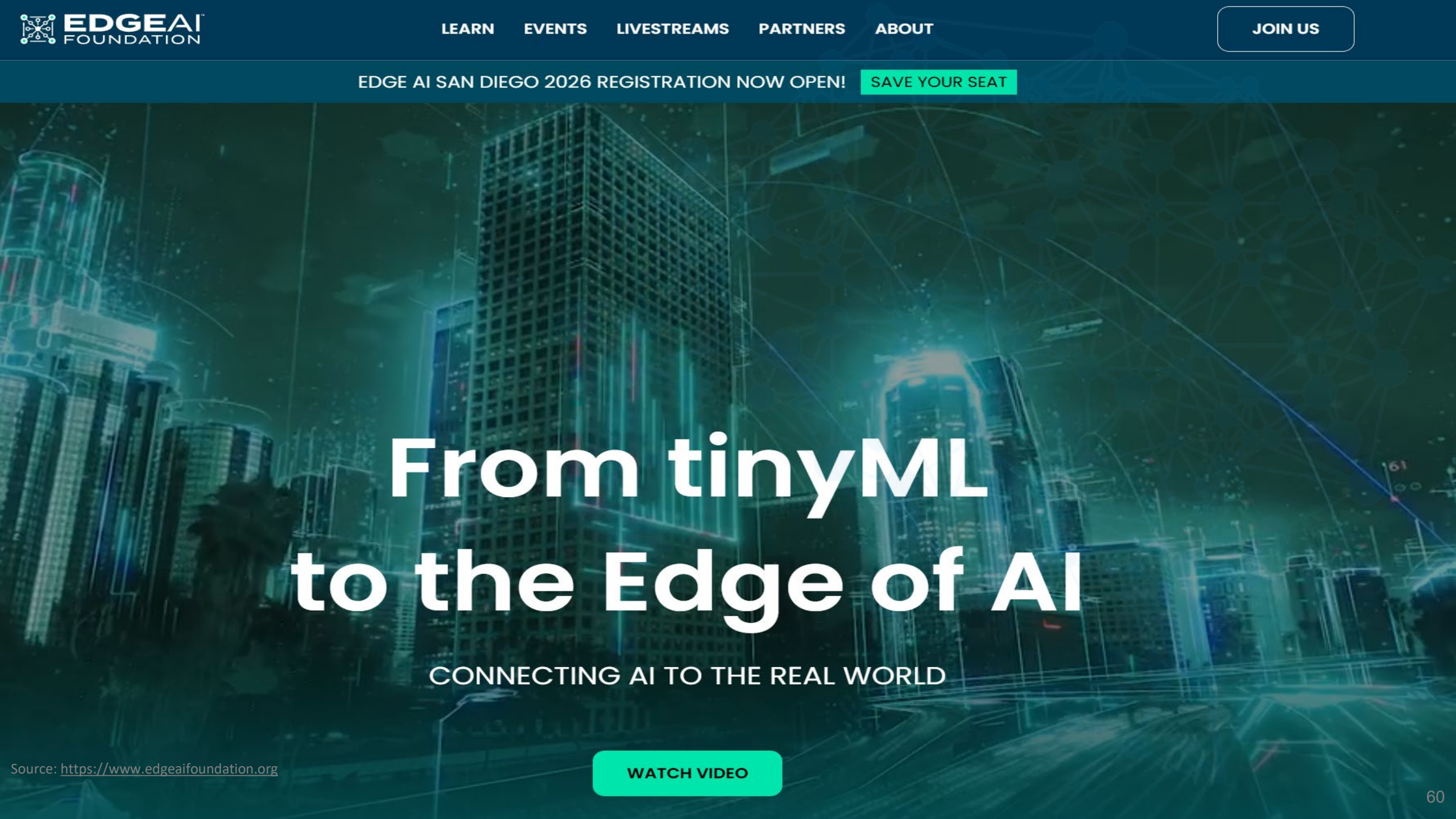
58

Source: https://www.edgeaifoundation.org/edgeai-content/the-2025-edge-ai-technology-report

The Edge AI Market is expected to reach USD 143.6 Billion by 2032



Source: https://market.us/



Source: https://www.edgeaifoundation.org

edge ai + vision ALLIANCE

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If you're building AI or vision-enabled products, you've come to the right place.

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Submit an entry today!

2026 Edge AI and Vision Product of the Year Awards

Honoring innovation and achievement in edge AI and computer vision building-block technologies

Submit an entry now!

The Latest

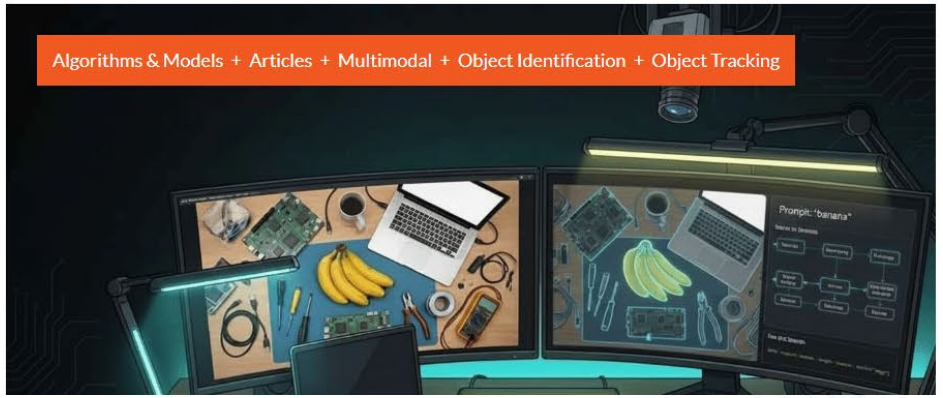
When DRAM Becomes the Bottleneck (Again): What the 2026 Memory Squeeze Means for Edge AI

January 12, 2026

Read More +

What is a Red Light Camera? A Quick Guide to Vision-Based Traffic Violation Detection

Featured Resources



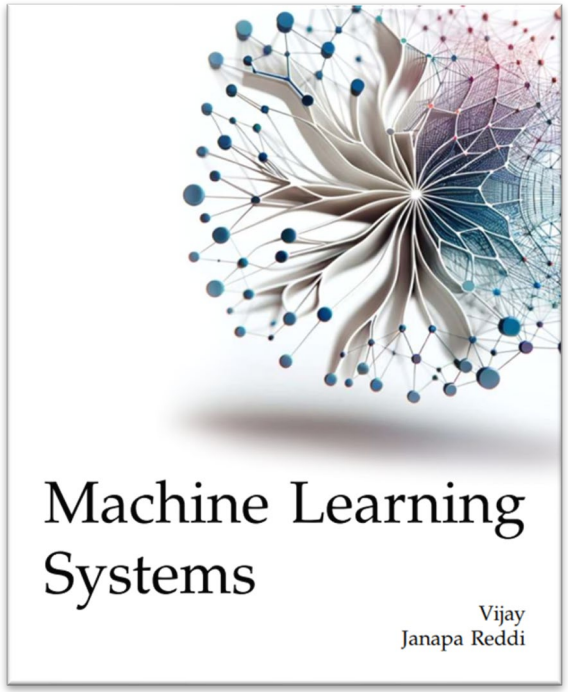
Source: https://www.edge-ai-vision.com

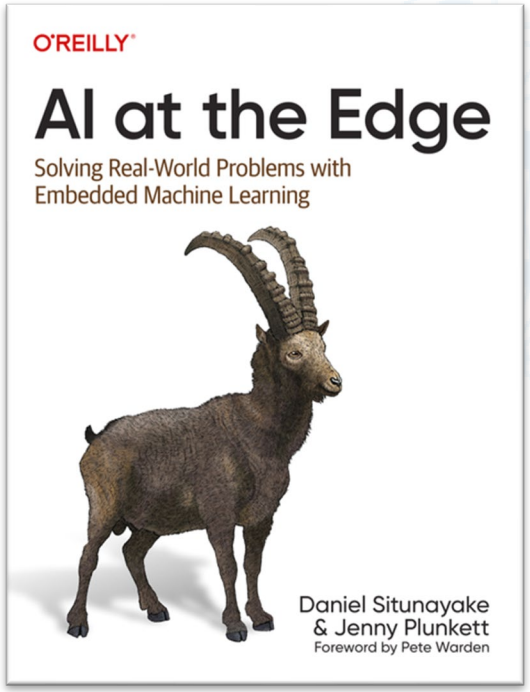
Course Topics

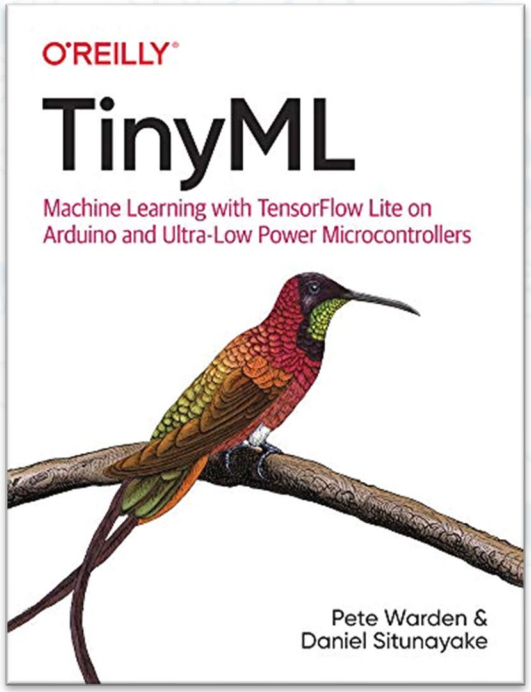
What will you learn in this course?

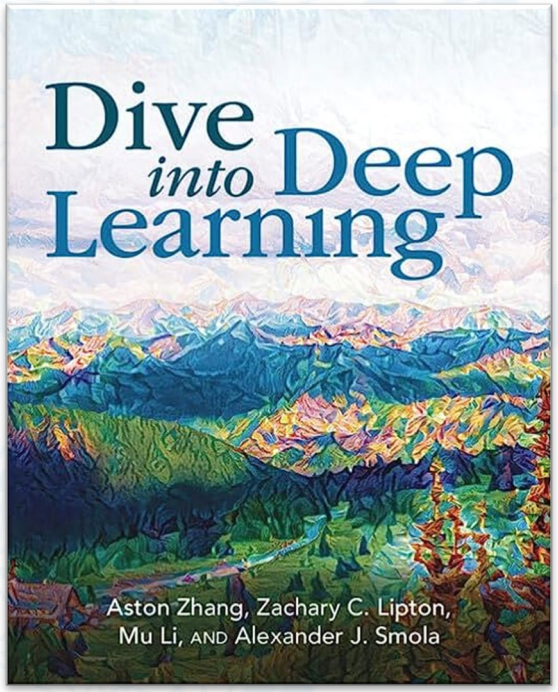
- Foundations of IoT, Accelerated Edge Computing, and Edge AI
- AI/ML and Computer Vision Fundamentals
- Tiny and Embedded Machine Learning
- Edge AI Hardware and Accelerators
- Edge AI Software Frameworks and Deployment Pipeline
- Model Compression and Optimization (Pruning, Quantization, Distillation)
- Federated and Distributed Learning for Edge Devices
- Generative and Agentic AI on Edge
- Sustainable and Energy-Efficient AI
- Case Studies in Smart Cities, Agriculture, and Healthcare
- Software and Libraries: Micro Python, OpenMV, TensorFlow Lite and LiteRT, PyTorch and ExecuTorch, and ONNX

Books and reference materials









Plus, hands-on tutorials and research papers

Grading

- Five programming assignments (5 × 10%): 50%
  - End-to-end human activity recognition system (e.g., fitness tracker) using a smart wearable kit
  - AI model compression using post-training quantization and quantization-aware training
  - Model pruning and sparsity techniques for efficient edge inference
  - End-to-end embedded computer vision system prototype
  - Federated learning algorithm implementation on edge devices and accelerators
- Course project: 30%
- Final examination: 20%

Prerequisites:

- Proficiency in Python and C programming
- Optional: Basics of AI/ML, programming microcontrollers and embedded systems, and IoT

Hardware Platforms

Arduino Tiny Machine Learning Kit

Arduino Nano 33 BLE Sense

OV7675 Camera

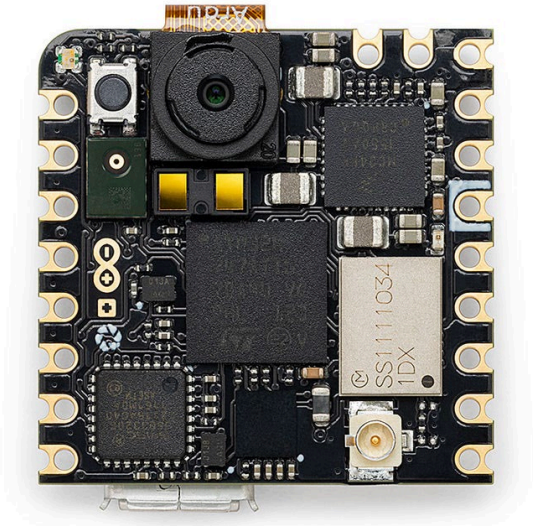
Arduino Tiny Machine Learning Shield

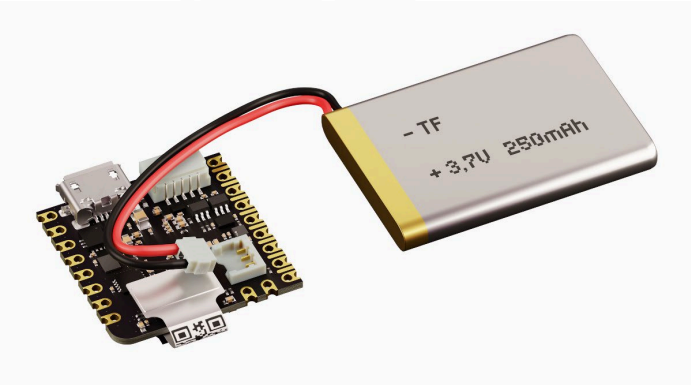
USB A to Micro USB Cable

Source: https://store.arduino.cc/products/arduino-tiny-machine-learning-kit

Hardware Platforms

Arduino Nicla Vision

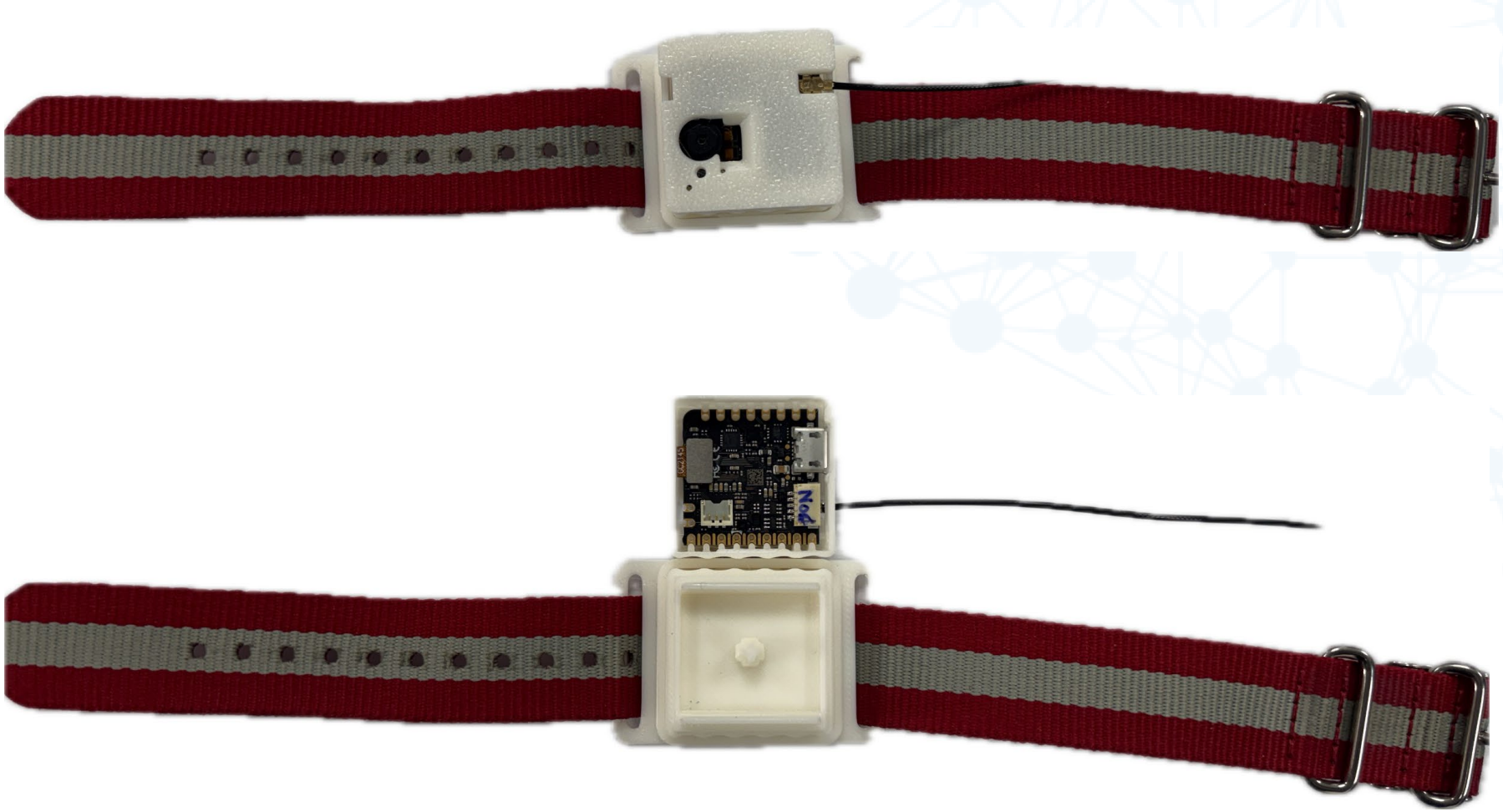




Microcontroller	•STM32H747AII6 Dual Arm® Cortex® M7/M4 IC:1x Arm® Cortex® M7 core up to 480 MHz •1x Arm® Cortex® M4 core up to 240 MHz
Sensors	•2 MP Color Camera •6-Axis IMU (LSM6DSOX) •Distance / Time Of Flight sensor (VL53L1CBV0FY/1) •Microphone (MP34DT05)
Power	•3.7V Li-po battery with Integrated battery charger and fuel gauge (MAX17262REWL)
Memory	2MB Flash / 1MB RAM 16MB QSPI Flash for storage
Connectivity	Wi-Fi / Bluetooth® Low Energy 4.2 (Murata 1DX - LBEE5KL1DX-883)

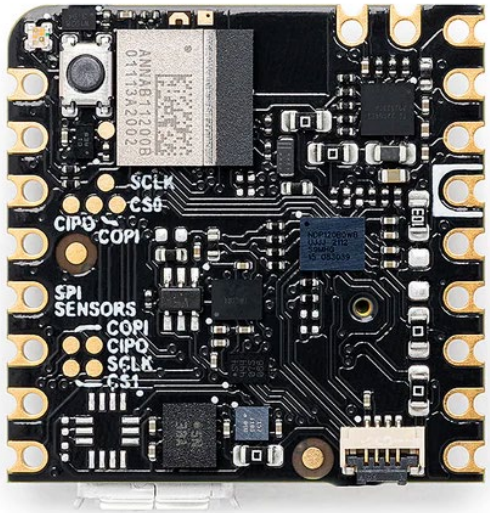
Source: https://docs.arduino.cc/hardware/nicla-vision/

Smart Wearable Kit using Nicla Vision



Hardware Platforms

Arduino Nicla Voice

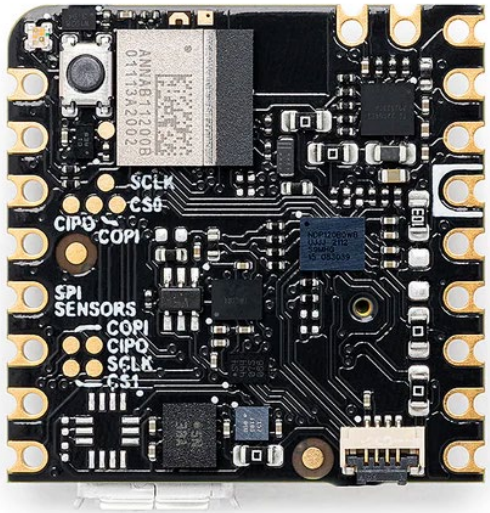


Microprocessor	•Syntiant® NDP120 Neural Decision Processor™ (NDP):1x Syntiant Core 2™ ultra-low-power deep neural network inference engine •1x HiFi 3 Audio DSP •1x Arm® Cortex® M0 core up to 48 MHz
Microcontroller	•Nordic Semiconductor nRF52832:64 MHz Arm® Cortex M4
Sensors	•High performance microphone (IM69D130) •6-Axis IMU (BMI270) •3-axis magnetometer (BMM150)
Memory	•512KB Flash / 64KB SRAM •16MB SPI Flash for storage •48KB SRAM dedicated for NDP120
Power	•3.7V Li-po battery with Integrated battery charger and fuel gauge (BQ25120AYFPR)
Connectivity	•Bluetooth® Low Energy (ANNA-B112)

Source: https://docs.arduino.cc/hardware/nicla-voice/

Hardware Resources Available

Arduino Nicla Sense ME



Microcontroller	64 MHz Arm® Cortex M4 (nRF52832)
Sensors	BHI260AP - **Self-learning AI smart sensor** with integrated accelerometer and gyroscope BMP390 - Digital pressure sensor, BMM150 - Geomagnetic sensor, BME688 - Digital low power gas, pressure, temperature & humidity sensor with AI
Connectivity	Bluetooth® 4.2
Power	Micro USB (USB-B), Pin Header, 3.7V Li-po battery with Integrated battery charger
Memory	512KB Flash / 64KB RAM, 2MB SPI Flash for storage, 2MB QSPI dedicated for BHI260AP

Source: https://docs.arduino.cc/hardware/nicla-sense-me/

Hardware Resources Available

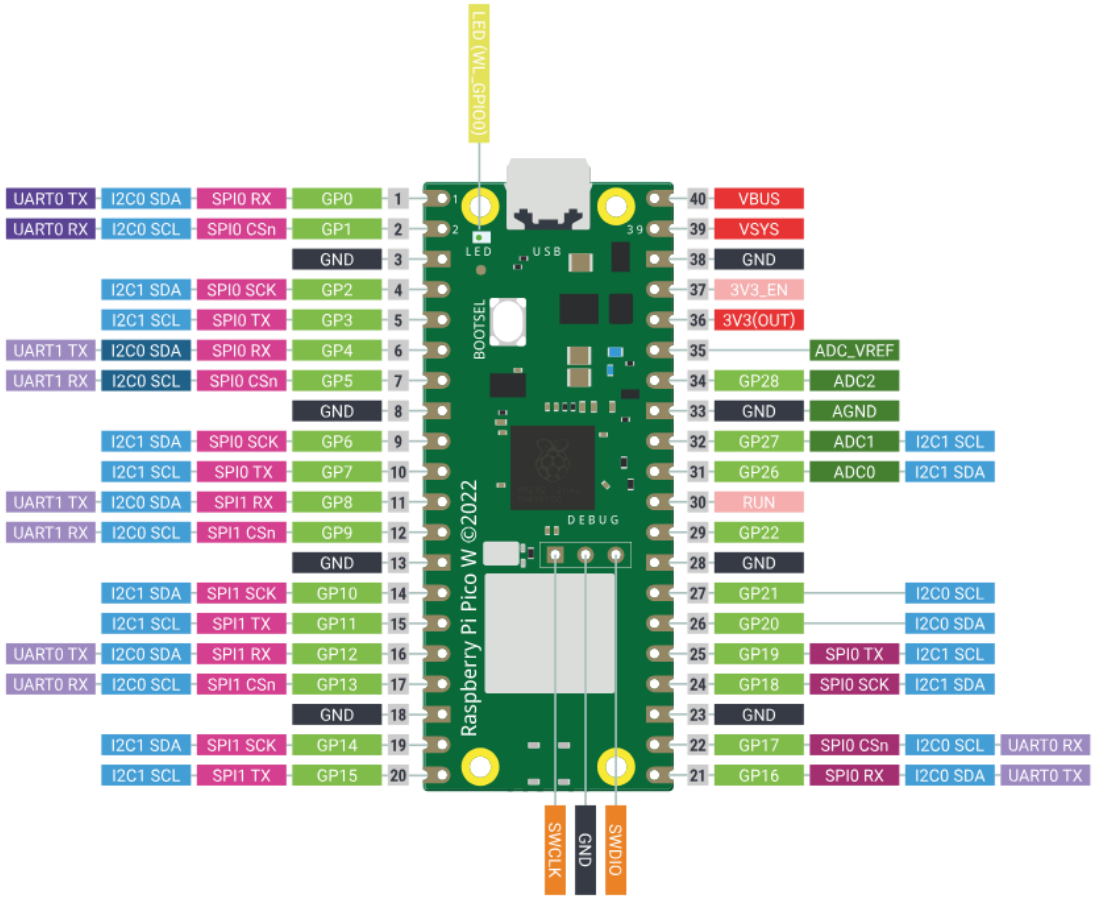
WIO Terminal

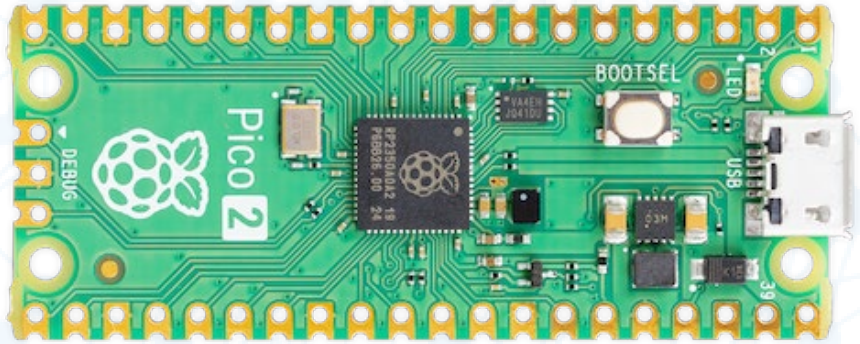
Main Chip	Core Processor	ARM® Cortex®-M4F running at 120MHz
	Memory	4 MB External Flash, 192 KB RAM
	Maximum Speed	200MHz
	External Flash	4MBytes
LCD Screen	Resolution	320x240
	Display Size	2.4inch
	Drive IC	ILI9341
Wireless	Wi-Fi	802.11 a/b/g/n 1x1, Dual Band 2.4GHz & 5GHz
	Bluetooth	Support BLE5.0
Built-in Modules	Accelerometer	LIS3DHTR
	Microphone	1.0V-10V -42dB
	Speaker	≥78dB @10cm 4000Hz
	Light Sensor	400-1050nm
	Infrared Emitter	940nm
Interface	MicroSD Card Slot	Maximum 16GB
	GPIO	40-PIN (Raspberry Pi Compatible)
	Supported Protocol	SPI, I2C, I2S, ADC, DAC, PWM, UART(Serial)
Operation Interface	5-Way Switch	
	Power/Reset Switch	

Source: https://www.seeedstudio.com/Wio-Terminal-p-4509.html

Hardware Resources Available

Raspberry Pi Pico W



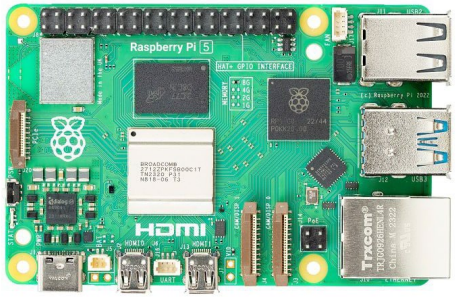


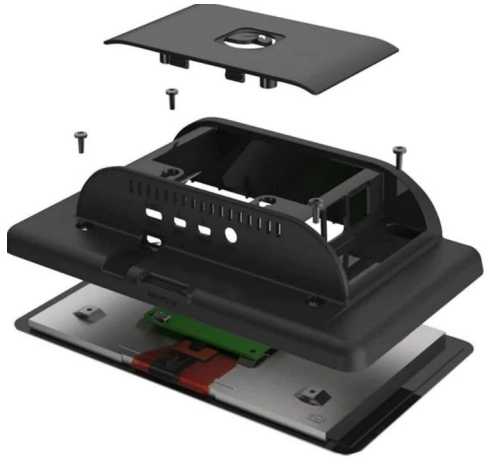
- Dual-core Arm Cortex M0+ processor, flexible clock running up to 133 MHz
- 264kB of SRAM, and 2MB of on-board flash memory
- Wireless (802.11n), single-band (2.4 GHz)
- Bluetooth 5.2
- **Ideal board for connecting external sensors!**

Source: https://www.raspberrypi.com/documentation/microcontrollers/pico-series.html

Edge AI PC

- Raspberry Pi 5 Model 8GB RAM
- NPU: Hailo-8 NPU - AI HAT+ 26 TOPS
- PI Touch Display 2
- Camera Module 3





Hardware Platforms

- reComputer J1010 Edge AI Device with Jetson Nano
- JetBot AI Kit

1. Powered by the quad-core ARM® Cortex®-A57 MPCore processor.
2. 128-core NVIDIA Maxwell™ GPU with 128 NVIDIA CUDA® cores delivers 0.5 TFLOPs (FP16).
3. RTC Connector
4. M.2E Connector
5. Module: JetSon Nano
6. USB Type: C power Connector
7. Rich peripherals including Gigabit Ethernet port, USB 3.0 and USB 2.0 Type-A ports, HDMI port.
8. Pre-installed NVIDIA official JetPack software, ready for cloud native application.

Source: https://robu.in/product/diy-nvidia-jetsonnano-development-learning-kit-jetbot/

Similar Courses

- edX tinyML Specialization (Harvard University) [Link]
- CS249r: Tiny Machine Learning (Harvard University) [Link]
- ESE 3600: Tiny ML (University of Pennsylvania) [Link]
- TinyML and Efficient Deep Learning Computing (MIT) [Link]
- Embedded Deep Learning & TinyML (Carnegie Mellon University) [Link]
- IoT and Tiny Machine Learning (Marquette University) [Link]
- Machine Learning for Embedding Devices (UNIFEI, Brazil)[Link]
- Introduction to Embedded Machine Learning (Edge Impulse) [Link]
- Computer Vision with Embedded Machine Learning (Edge Impulse) [Link]
- Edge AI and Robotics (NVIDIA) [Link]
- AI on the Edge with Computer Vision (Intel) [Link]
- Machine Learning at the Edge on Arm: A Practical Introduction (Arm)[Link]

References

1. NVIDIA Edge AI and Robotics Teaching Kit [Link]
2. Machine Learning Systems [Link]
3. AI at the Edge Book [Link]
4. TinyML Courseware [Link]
5. Edge Intelligence: Paving the Last Mile of Artificial Intelligence With Edge Computing, Zhou et al. 2019 [Link]
6. Tiny Machine Learning: Progress and Future, Lin et al. 2023 [Link]
7. TinyML and Efficient Deep Learning Computing [Link]

Readings

Edge Intelligence: Paving the Last Mile of Artificial Intelligence With Edge Computing

This article conducts a comprehensive survey of the research efforts on edge intelligence. It provides an overview of the architectures, frameworks, and emerging key technologies for deep learning model toward training and inference at the network edge.

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