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* Wikipedia: Edge computing
* News/Report: McKinsey — “Edge AI: Scaling AI at the point of data generation”

Edge AI for IoT—Latency, Energy, and Real-World Use Cases

Overview

Edge AI runs models near where data is produced—on sensors, gateways, and phones—rather than shipping every signal to the cloud. The motivation is straightforward: **lower latency**, **lower bandwidth**, and **better privacy**. This briefing explains the constraints that shape edge systems, practical optimization techniques, and concrete use cases across vision, speech, and maintenance.

Why the Edge?

* **Latency**: On-device decisions in **tens of milliseconds** enable safety features (e.g., obstacle avoidance).
* **Availability**: Works offline or with intermittent connectivity (factory floors, ships, rural settings).
* **Privacy & cost**: Raw video/audio stays local, cutting cloud egress costs and exposure surface.

Edge does not replace cloud; it complements it. The cloud trains large models, aggregates telemetry, and coordinates over-the-air (OTA) updates; the edge does the last-mile inference and lightweight learning.

Compute and Energy Constraints

Edge devices range from microcontrollers with **tens of kilobytes** of RAM to phones and gateways with multi-core CPUs, GPUs, or NPUs:

* **MCUs (TinyML)**: e.g., ARM Cortex-M class; models must fit in **<1 MB** of flash and inference in **<10 ms** for wake words.
* **Embedded SoCs**: ARM A-class, NPUs (e.g., 1–10 TOPS); enough for **real-time 30 FPS** object detection at 320×320.
* **Mobile/PC**: dedicated NPUs (10s–100s TOPS) for on-device transcription, translation, and small-LLMs.

Power budgets drive architecture choices: an MCU sipping **milliwatts** can run months on coin cells; an embedded SoC may live under **5–15 W** in a kiosk; mobile devices must keep thermal headroom for user comfort.

Optimization Toolbox

Quantization

Convert weights/activations from FP32 to **int8 or int4**. Int8 often yields **2–4× speedups** with small accuracy drops; **per-channel** quantization recovers quality. Post-training quantization (PTQ) is fast; quantization-aware training (QAT) performs better on tough models.

Pruning and Sparsity

Structured pruning (drop channels/heads) and unstructured sparsity (zeros in weight matrices) shrink models and bandwidth. Hardware support varies; some NPUs exploit **>50% sparsity** for additional speedups.

Distillation

Train a **student** to mimic a larger **teacher** model. For speech and vision, distilled students keep most accuracy with **30–70%** fewer parameters.

Compilation and Operators

Use vendor compilers (e.g., NNAPI, Core ML, TensorRT) to fuse ops and map to accelerators. For portability, keep models to a **well-supported op set** and avoid custom kernels unless necessary.

Streaming and Windows

For audio and sensor data, process streaming windows (e.g., 20–40 ms frames) so memory usage stays bounded. Maintain small **ring buffers** of features rather than raw data.

Architecture Patterns

* **On-device only**: All compute local; upload only summaries. Good for privacy-critical tasks (health wearables).
* **Edge gateway**: Cameras stream to a nearby gateway with a stronger NPU; gateway runs detection and sends events upstream.
* **Split inference**: Early layers on device, later layers in the cloud when connectivity is good; fallback to local “good enough” models otherwise.
* **Federated learning**: Devices train small updates on local data; a server aggregates gradients. Works well for personalization (wake words, keyboard).

Use Cases

Vision: Quality Inspection and Safety

A conveyor camera detects defects and ejects faulty parts. Requirements:

* **Latency**: <50 ms to actuate a gate in time.
* **Model**: Tiny object detector (e.g., MobileNet-SSD class) at 320×320 or 416×416.
* **Ops**: Background adaptation for lighting shifts; sporadic cloud review of hard cases.

In safety zones, people detection triggers alarms when a person crosses into a robot’s workspace. Privacy is preserved by **not** storing faces; only bounding boxes and event logs leave the site.

Speech and Audio: Wake Words and ASR

* **Wake word**: 10–20 ms frames, **false reject** rate tightly controlled (<2–3%) so users don’t repeat commands; **false accepts** minimized to avoid accidental triggers.
* **On-device ASR**: Small conformers transcribe locally with p95 latency under a second for short utterances. A **RAG-style** on-device cache (keywords, contacts) boosts rare-word accuracy without cloud calls.

Predictive Maintenance: Vibration and Motor Health

Edge devices sample accelerometers and current sensors at a few kHz. Models classify bearing faults or imbalance from frequency features. Benefits include **reduced unplanned downtime** and targeted maintenance windows. Devices push only anomalies upstream, saving bandwidth by orders of magnitude.

Data and Retrieval at the Edge

Even edge systems benefit from **retrieval**:

* Cache **on-device embeddings** of recent sensor patterns; when an anomaly arises, retrieve the most similar past cases (by **cosine** similarity) for operator context.
* Store small **vector-stores** locally (hundreds to thousands of vectors) to keep comparisons fast without cloud access.
* Use **MMR** when surfacing past incidents, so technicians see diverse precedents rather than five near-duplicates.

Observability and Operations

* **Shadow mode**: Log predictions next to human labels before flipping to active control.
* **Drift detection**: Monitor input stats (brightness, noise, vibration spectra).
* **OTA updates**: Roll out to 1%, 10%, then 100% with rollback.
* **Security**: Signed model bundles, secure boot, and **zero-trust** networking on gateways.

Costing and Sizing

A rough budgeting rule: each additional watt of continuous draw on battery devices can cut life by **days to weeks** depending on capacity. For mains-powered kiosks, model size affects BOM via RAM and NPU requirements—**int8 models** can fit in **¼ the RAM** versus FP32, enabling cheaper SKUs.

What’s Next

Expect more **NPUs on commodity hardware**, standardized execution APIs, and

distilled LLMs running entirely on phones or gateways for short instructions and summaries. Multimodal fusion—combining camera, audio, and environmental sensors—will improve robustness without round-tripping to the cloud.

Key Takeaways

* Edge AI trades cloud scale for **latency, privacy, and cost** advantages.
* Quantization, pruning, and distillation are the big three levers for fitting models under tight power/compute budgets.
* Real deployments blend on-device, gateway, and cloud roles; OTA and observability are essential.
* Vision, speech, and maintenance deliver near-term ROI with straightforward metrics.
* Small **vector stores** and **retrieval** on device make diagnostics and operator UX markedly better.