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SNAP-UQ: Self-Supervised Next-Activation Prediction for Single-Pass Uncertainty in TinyML

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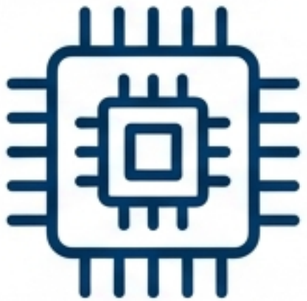
SNAP-UQ: Self-Supervised Next-Activation Prediction for Single-Pass Uncertainty

Reliable, State-Free Monitoring for Edge AI

The Core Definition	The Value Proposition & Impact
SNAP-UQ is a label-free uncertainty estimation mechanism designed specifically for microcontrollers (MCUs). It derives uncertainty not from the final softmax output, but from the network's internal feature dynamics.	■ **Single-Pass**: No ensembles, multiple passes, or Monte Carlo sampling. ■ **State-Free**: Zero temporal buffers; minimizes RAM usage. ■ **Integer-Friendly**: Fully compatible with Int8 quantized inference (CMSIS-NN). ■ **Impact**: Enables autonomous monitoring on milliwatt-scale hardware (Cortex-M4/M7).

Motivation: The TinyML Constraint Conflict

The Hardware Envelope



- **Target Devices:** Low-power MCUs (STM32L4, STM32F7)
- **Memory Budget:** <256KB Flash, <64KB SRAM
- **Compute Budget:** Milliwatt power; Real-time inference

The Safety Requirement

- **Corrupted-in-Distribution (CID):** Sensor noise, gain shifts, lighting changes.
- **Out-of-Distribution (OOD):** Anomalous inputs (unknown objects/speech).

The Conflict: Standard reliability methods (Ensembles/Bayesian) require multiple passes, state buffers, or large footprints.

TinyML needs a metric that is intrinsic to the single forward pass.

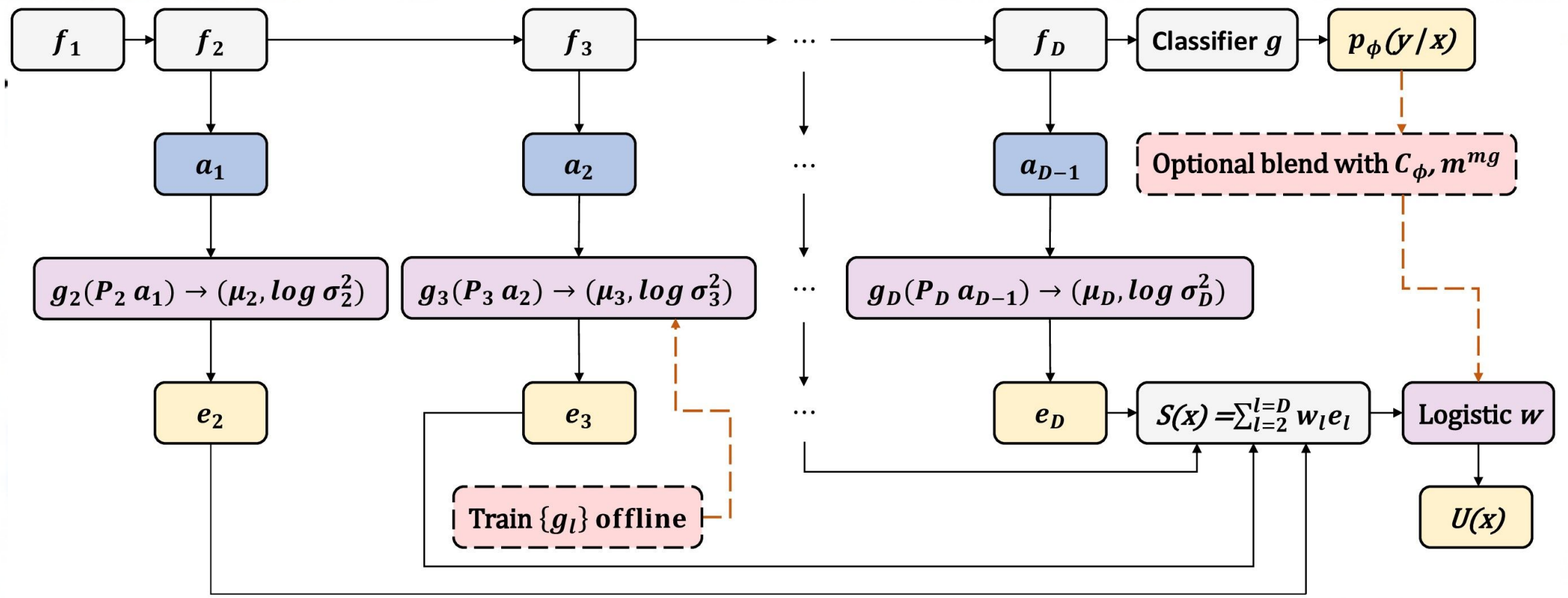
Problem: Limitations of Current Uncertainty Methods on MCUs

Deep Ensembles & MC Dropout	• **Latency Tax:** Requiring M forward passes multiplies latency/energy by factor M. • **Memory Tax:** Ensembles require storing M sets of weights. • **Failure:** Triggers Out-Of-Memory (OOM) errors on Small-MCUs.
Softmax Confidence (The Baseline)	• **"Peaky" Behavior**: Deep networks are overconfident on OOD samples in high-density regions. • **Late Detection**: Captures errors only at the output. Fails to detect internal feature distortions early.
Early-Exit Ensembles	• **Overhead**: Branching architectures and control logic add 10-25% overhead. • **Complexity**: Hard to optimize for linear instruction streams.

Architecture: The SNAP-UQ Pipeline

Concept: The "Tap" System

SNAP-UQ attaches lightweight side-branches to a frozen backbone at specific depths (mid-block and penultimate).



1. **Tap:** Extract activation $a_{\ell-1}$.
2. **Project (P_ℓ):** Compress using 1x1 conv + GAP to low-rank summary z_ℓ.
3. **Predict (g_ℓ):** Tiny MLP predicts statistics of the *next* activation.
4. **Compare:** Calculate mismatch between predicted and actual a_ℓ.

Methodology: Next-Activation Prediction

The Core Hypothesis: If a network "understands" an input, the transformation from layer $\ell - 1$ to ℓ is predictable.

- **In-Distribution (ID):** Features evolve smoothly.
- **Corrupted/OOD:** Internal evolution is disrupted. Actual a_ℓ deviates from the prediction.

Self-Supervised Supervision:

- **Signal:** The network's *own* future activation.
- **Query:** "Given features at $\ell - 1$, what should ℓ look like?"

The Predictor Heads (g_ℓ):

- **Input:** Low-rank projection z_ℓ.
- **Output:** Mean (μ_ℓ) and Log-Variance ($\log \sigma_\ell^2$).
- **Cost:** Approx. 2% of backbone FLOPs.

Math I: Conditional Density Modeling

$$p_\theta(a_\ell | a_{\ell-1}) = \mathcal{N}(\mu_\ell, \mathrm{diag}(\sigma_\ell^2))$$

Components

- $\mu_\ell = g_\mu(P_\ell a_{\ell-1})$: The expected value of the next activation.
- $\sigma_\ell^2 = \mathrm{softplus}(g_\sigma(P_\ell a_{\ell-1})) + \epsilon$: The expected variance (uncertainty).

Why Diagonal Gaussian?

- **Efficiency**: Full covariance requires $O(d^2)$. Diagonal requires $O(d)$.
- **Independence**: Sufficient for detecting feature disruptions without expensive matrix ops on MCUs.

Math II: Surprisal Calculation

Measuring the “Surprisal” (Negative Log-Likelihood) of the actual activation.

$$u_\ell(x) = (a_\ell - \mu_\ell) \odot \sigma_\ell^{-1}$$

Formula of Quadratic Energy (Surprisal):

$$e_\ell(x) = \|u_\ell(x)\|_2^2 = \sum_{i=1}^{d_\ell} \left(\frac{a_{\ell,i} - \mu_{\ell,i}}{\sigma_{\ell,i}} \right)^2$$

Mean Mismatch: Feature value isn’t what was predicted.

Scale Normalization:
Penalize errors in stable channels; be lenient in noisy ones.

Result: $e_\ell(x)$ spikes when the feature transition is anomalous relative to the training distribution.

Math III: Aggregation and Uncertainty Mapping

Step 1.
Dimension Normalization

$$\bar{e}_\ell(x) = \frac{1}{d_\ell} e_\ell(x)$$

Normalize energy by layer dimension d_ℓ for comparison.

Step 2.
Aggregation

The SNAP score $S(x)$ is a weighted sum across tapped layers $\mathcal{S}$:

$$S(x) = \sum_{\ell \in \mathcal{S}} w_\ell \bar{e}_\ell(x)$$

Where w_ℓ are layer-specific weights for combining scores.

Step 3.
Uncertainty Mapping ($S(x) \to U(x)$)

Mapping Recipe

- **Logistic:** $U(x) = \sigma(\beta_0 + \beta_1 S(x) + \beta_2 m(x))$ (Recommended for in-distribution calibration; uses sigmoid function σ.)
- **Isotonic Regression:** Non-parametric monotone mapping for strict calibration. (Recommended for fixed coverage monitoring; preserves ordering.)
- **Optional:** $m(x)$ blends classifier confidence (C_ϕ) for added separability. (e.g., top 2 logit margin or max softmax. When m is unavailable, set $\beta_2 = 0$.)

Theory I: Relation to Depth-wise NLL

Proposition 2.1 (Surprisal–Likelihood Equivalence)

Under the diagonal-Gaussian model, the negative log-likelihood of activation a_ℓ given $a_{\ell-1}$ is:

$$-\log p_\theta(a_\ell|a_{\ell-1}) = \frac{1}{2}e_\ell(x) + \frac{1}{2}\sum_{i=1}^{d_\ell}\log\sigma_{\ell,i}^2 + \text{const}$$

Implications:

- **Equivalence:** Minimizing the SNAP-UQ objective ≈ Maximizing likelihood of feature transitions.
- **Affine Transform:** The Score $S(x)$ is an affine transformation of the depth-wise NLL.
- **Inference:** High $S(x)$ strictly implies a lower conditional likelihood of the observed activations.

Theory II: Relation to Conditional Mahalanobis

Proposition 2.2

If feature dynamics are approximately linear ($\mathbf{a}_\ell \approx \mathbf{W}_\ell \mathbf{a}_{\ell-1} + \mathbf{b}_\ell$), then $e_\ell(\mathbf{x})$ is the squared Mahalanobis distance to the conditional mean:

$$e_\ell(\mathbf{x}) = \mathrm{MD}^2_{\Sigma^2_\ell}(\mathbf{a}_\ell, \mathbf{W}_\ell \mathbf{a}_{\ell-1} + \mathbf{b}_\ell)$$

Class-wise Mahalanobis (State-of-the-Art Baseline)	SNAP-UQ (Conditional)
• Compares $\mathbf{a}_\ell$ to static class centroid $\bar{\mu}_c$. • Fails if features shift but remain near centroids.	• Compares $\mathbf{a}_\ell$ to dynamic sample-specific prediction. • Sensitive to shifts that break layer-to-layer mapping.

Affine Invariance: Score is robust to Batch-Norm-like per-channel rescaling.

Implementation: TinyML Optimization

Int8 Quantized Weights

CMSIS-NN Kernels (Int32 Accumulators)

LUT Approximation

- Use small 256-entry Look-Up Table for $\exp\left(-\frac{1}{2}\log\sigma^2\right)$.
- Avoids expensive Floating Point math.

Footprint

- **Flash:** +10-30 KB (weights for tiny heads).
- **RAM:** Zero temporal buffering. Stream-based computation.

Experimental Setup

Hardware

- **Small-MCU:** STM32L4 (*Computer Modern*, Cortex-M4, 256KB Flash, 64KB RAM)
- **Big-MCU:** STM32F7 (*Computer Modern*, Cortex-M7, 512KB Flash, 216 MHz)

Backbones & Data

- **Vision:** ResNet-8 on **CIFAR-10 / TinyImageNet**
- **Audio:** DS-CNN on **SpeechCommands**

Baselines

- **Single-Pass:** Softmax Entropy, Max-Prob, Class-wise Mahalanobis
- **Multi-Pass:** MC Dropout (5x), Deep Ensembles (3-5x)
- **Early-Exit:** EE-Ensembles

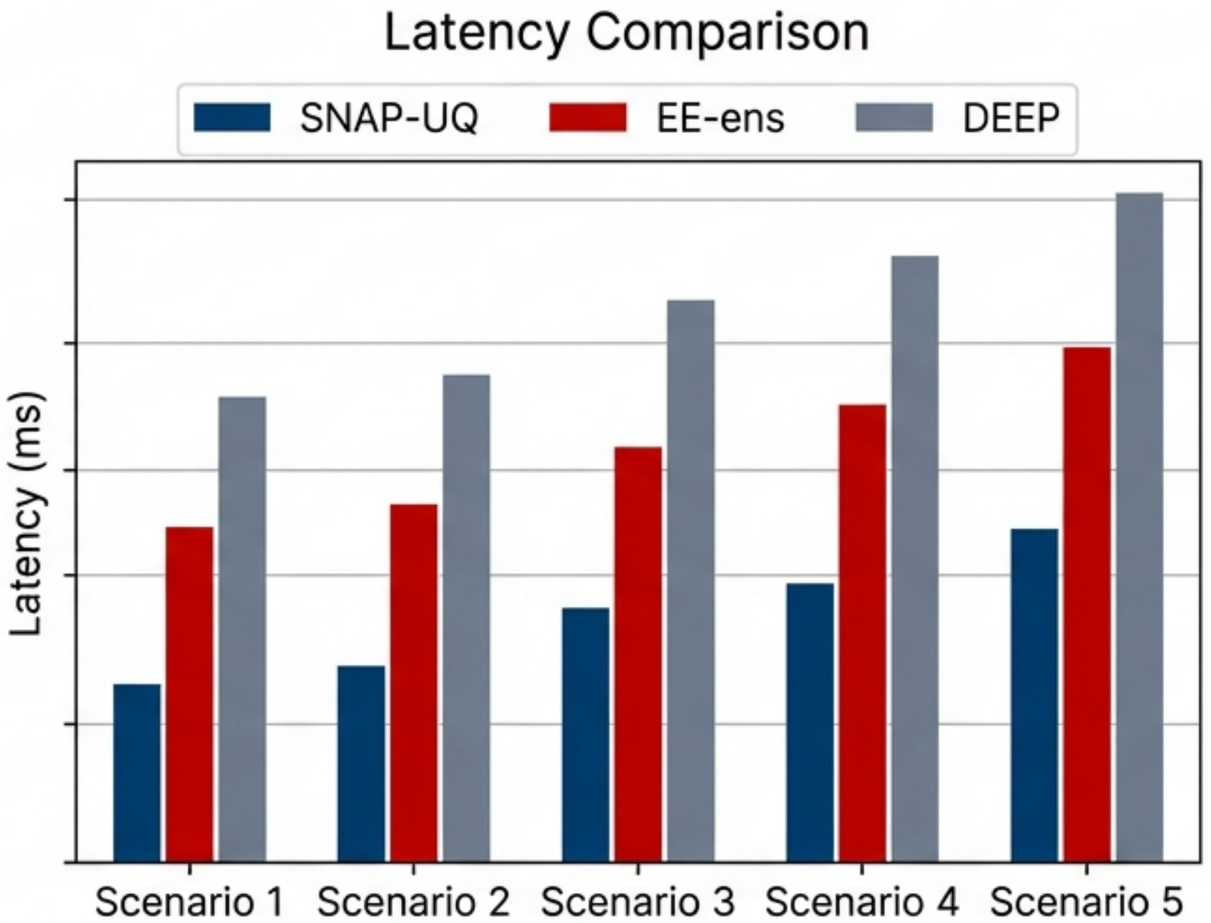
Results: Efficiency and Deployability

Flash & Memory:

- **Small-MCU**: Deep Ensembles & MC Dropout trigger **OOM (Out-of-Memory)**.
- SNAP-UQ fits comfortably (40-60% smaller than Ensembles).

Latency:

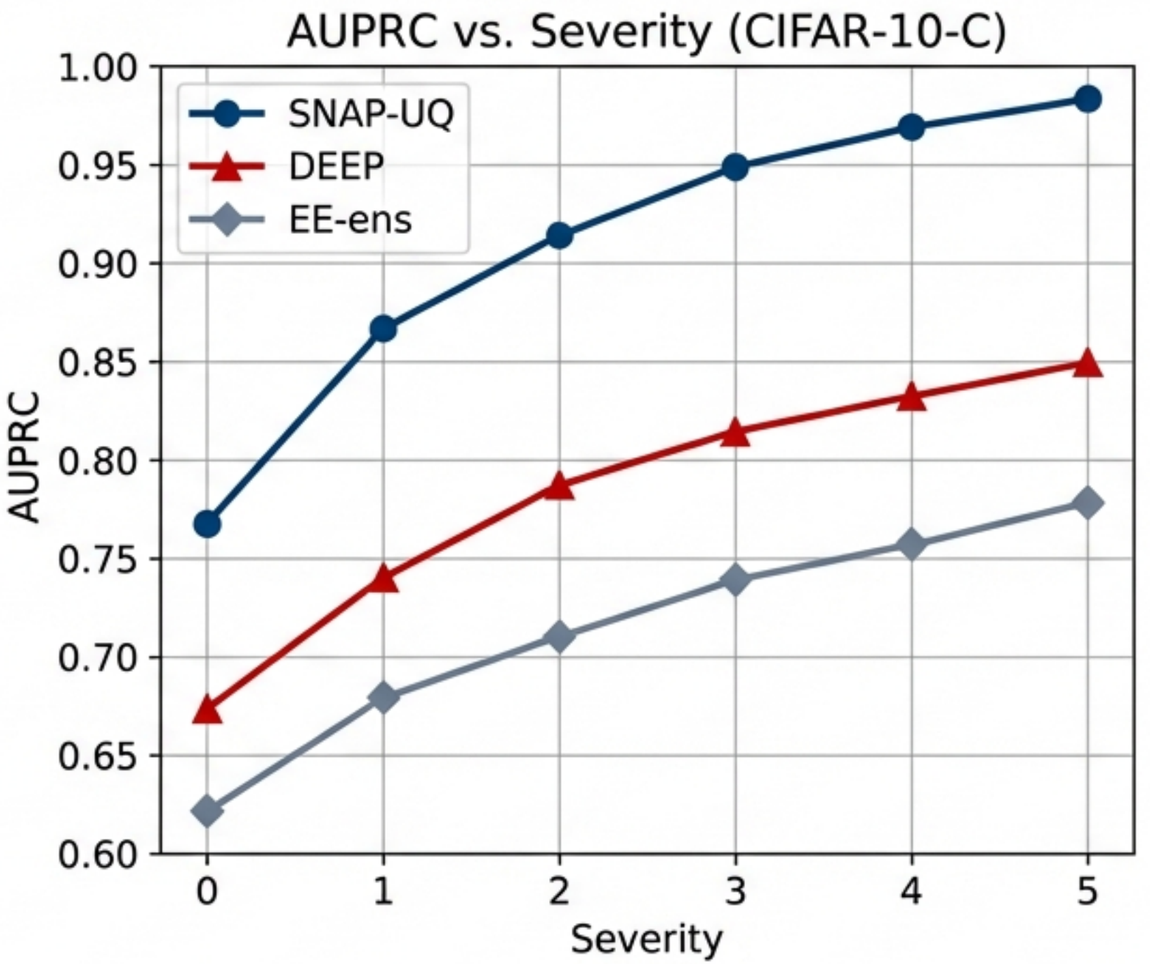
- **Speedup:** 25–35% faster than Early-Exit Ensembles.
- **Overhead:** <10% added to vanilla backbone.



Results: Robustness on Corrupted Streams

Metric: AUPRC (Area Under Precision-Recall Curve) on corrupted streams (CID).

- **Severity Scaling:** SNAP-UQ performance scales best as corruption severity increases.
- **Detection Delay:** Detects failure events **15-20 frames earlier** than Softmax Entropy.
- **Comparison:** Outperforms Deep Ensembles on failure detection despite single-pass constraint.



Conclusion: Certainty in Constraints

Key Contribution:

SNAP-UQ provides the first viable path for reliable, uncertainty-aware monitoring on ultra-constrained hardware (Cortex-M4).

The Paradigm Shift:

From: **Output Confidence** (Softmax) or **External Checks** (Ensembles)

To: **Internal Consistency** (Next-Activation Prediction)

Summary:

- **State-Free**: No buffers.
- **Single-Pass**: Minimal latency.
- **Label-Free**: Detects anomalies without online supervision.

Enabling autonomous edge devices to know *when they don't know*.

Thank You

- Acknowledgments
- Code: https://github.com/Ism-ail11/SNAP-UQ

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