



Photonic Neural Network Frontend for Automatic Modulation Classification



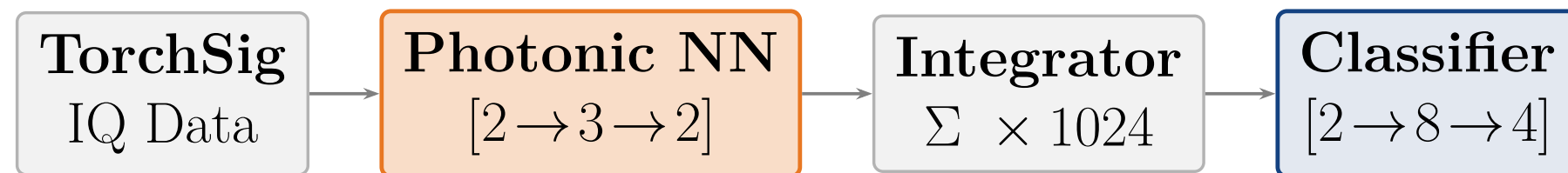
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Summary

- Silicon photonic **micro-ring resonators (MRRs)** can perform neural network inference in the analog domain — we validate this is sufficient for **Automatic Modulation Classification (AMC)**.
- **15 MRRs (2-3-2)** achieves **97%** accuracy across four classes (OOK, BPSK, QPSK, 8PSK) — realizable on current fabricated chips.
- **Nonlinearity essential:** linear baseline = 60% requiring ReLU for accurate classification.
- **Scaling pays off:** 2-8-2 (40 MRRs) reaches 100% at 20 dB SNR; 2-8-4 (56 MRRs) improves impairment robustness from 46% → 68%.
- **Channel impairments** are the open challenge — motivating physical chip validation and impairment-robust training as future work.

Pipeline and Photonic NN Design



The **Photonic NN** operates continuously in the analog domain — the simulation discretizes this to 1024 IQ samples per frame, each representing one time step at the operating sample rate. The **Classifier** evaluates once per frame.

Hardware constraints on the Photonic NN:

- **DAC quantization:** weights clamped to $[-1, 1]$ and quantized to 4096 levels (12-bit)
- **ReLU** in Layer 1 models the nonlinear MRR optical response; Layer 2 is linear (no activation).
- **Integrator** gives the system temporal context
- All three stages are **trained jointly** end-to-end via cross-entropy loss, with a Straight-Through Estimator (STE).

Data Generation and Training:

- **1000 training frames** and **200 test frames** per class, generated independently with no overlap
- Trained for **200 epochs** using the **Adam optimizer** with learning rate 1×10^{-3} and cross-entropy loss.

Background

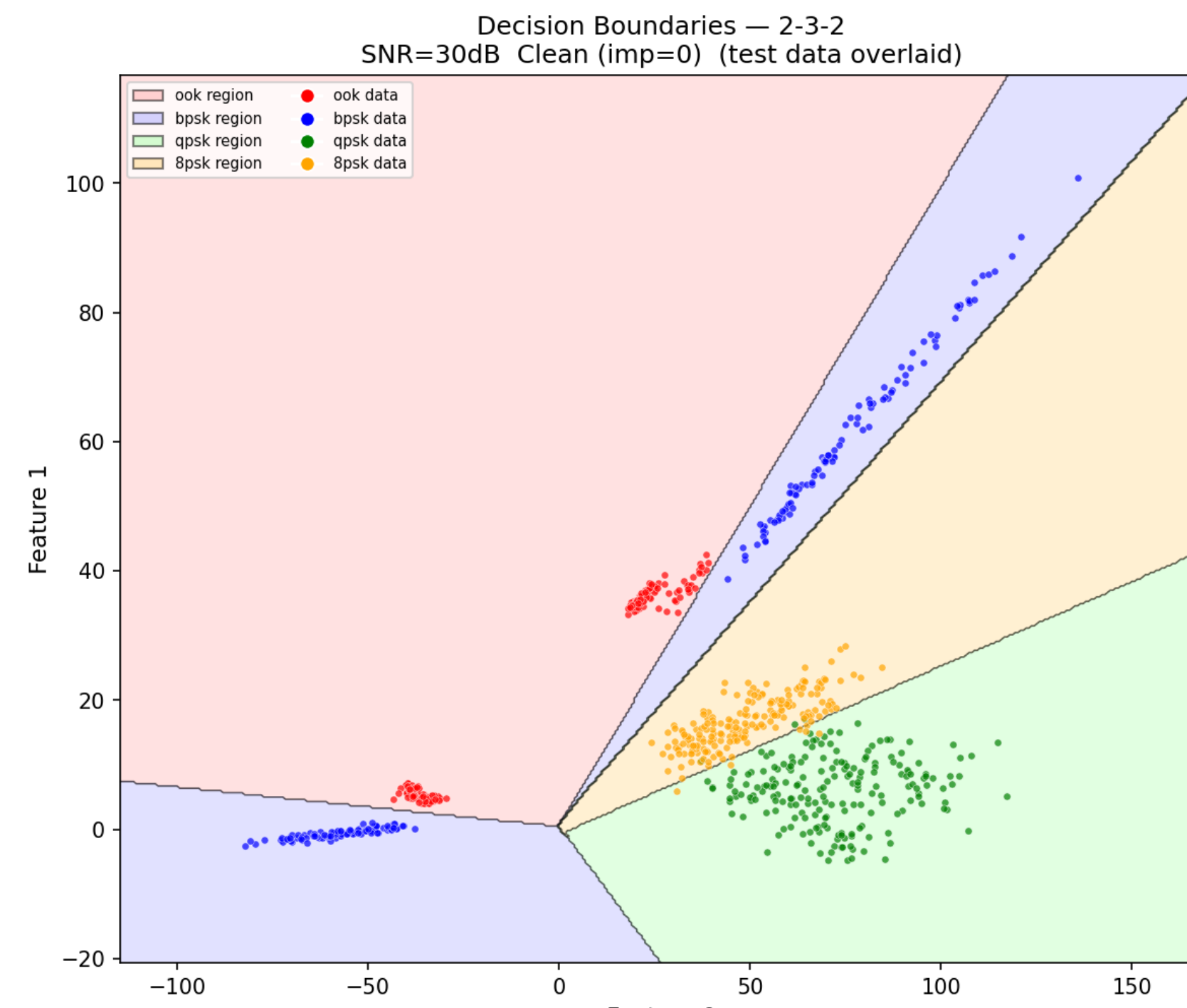
Different modulation types are discriminable by their **statistical moments**. Since a moment is defined as an integral of a function of the signal it maps naturally onto a three-stage photonic system and thus can be used for AMC (Lederman, 2025). This work validates this in simulation.

$$y = f\left(\int g(s(t)) dt\right)$$

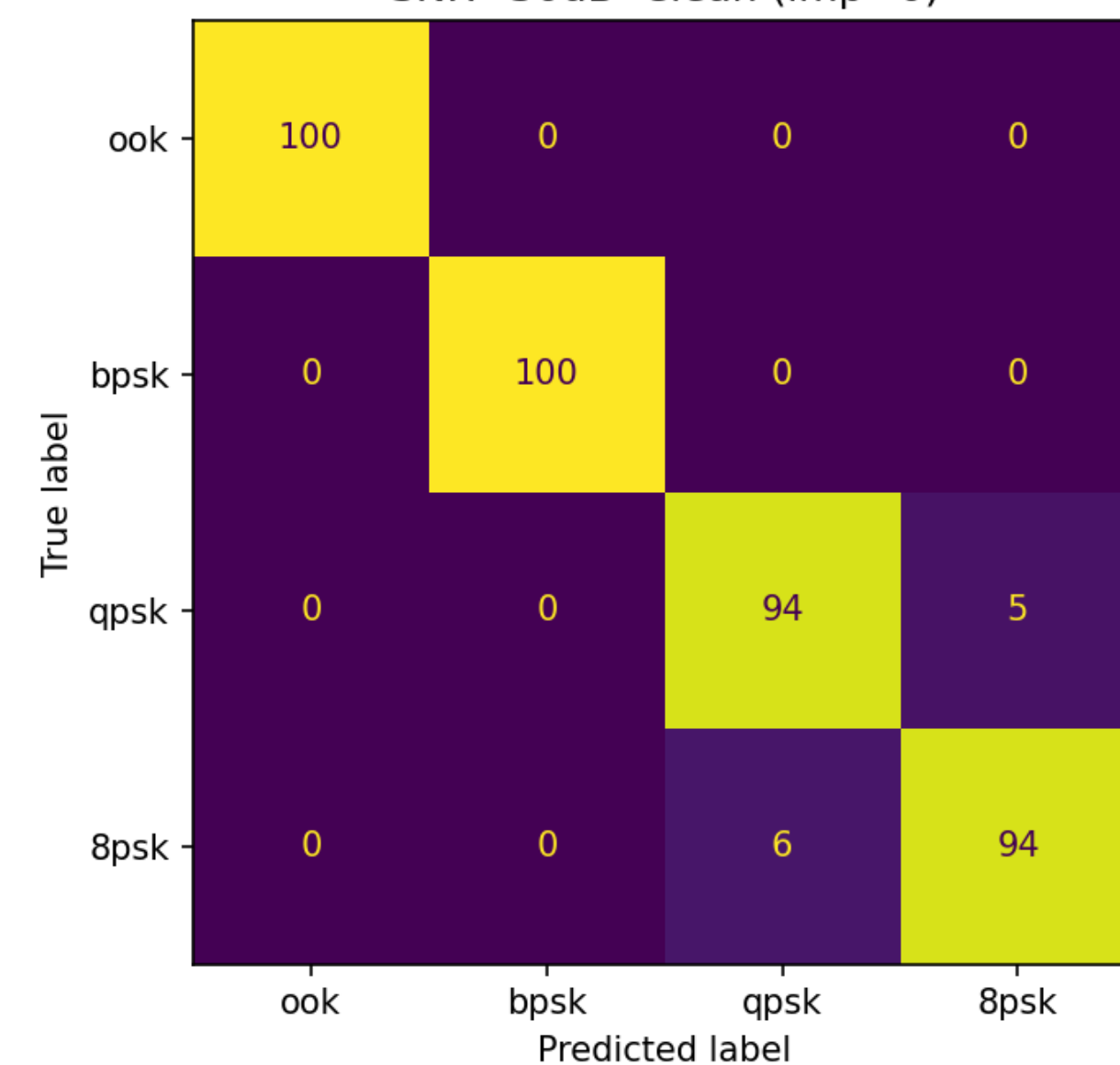
$g(\cdot) \rightarrow$ Photonic NN $\int dt \rightarrow$ Integrator $f(\cdot) \rightarrow$ Classifier

Architecture and Results

Topology	MRRs	Nonlinear?	Accuracy
2-2 (linear)	4	No	60.2%
2-2-2	10	Yes	83.2%
2-3-2	15	Yes	97.0%
2-8-2	40	Yes	~100%
2-8-4	56	Yes	~100%



Confusion Matrix — 2-3-2 | acc 0.970
SNR=30dB Clean (imp=0)



SNR & Impairment Robustness

SNR (2-3-2)	Acc.	Impairment (2-3-2)	Acc.
30 dB	97.0%	Clean	97.0%
20 dB	94.1%	Cabled	58.2%
10 dB	76.6%	Wireless	46.4%

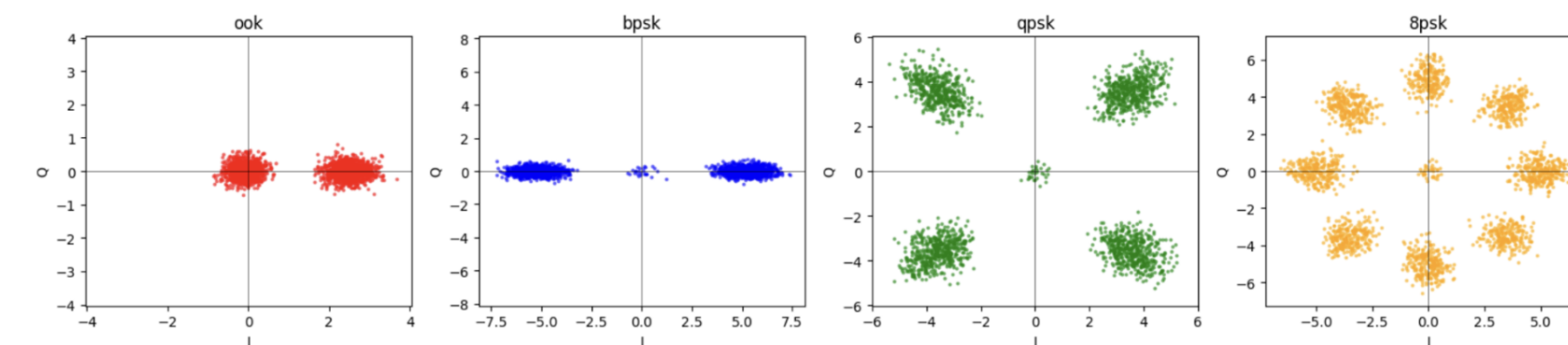


Figure 1: | SNR = 30 dB | *Imp: -1 | Symbol Matched Sampling

*TorchSig modified to remove all channel effects to depict idealized signal.

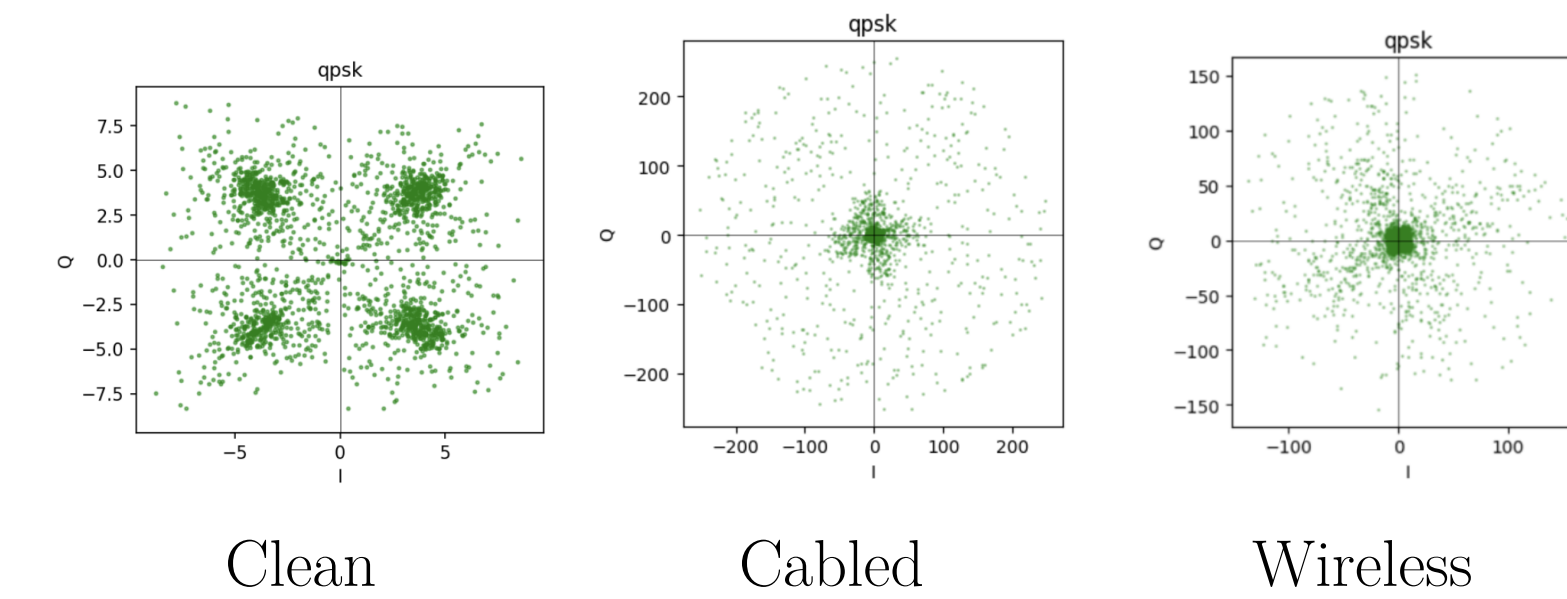
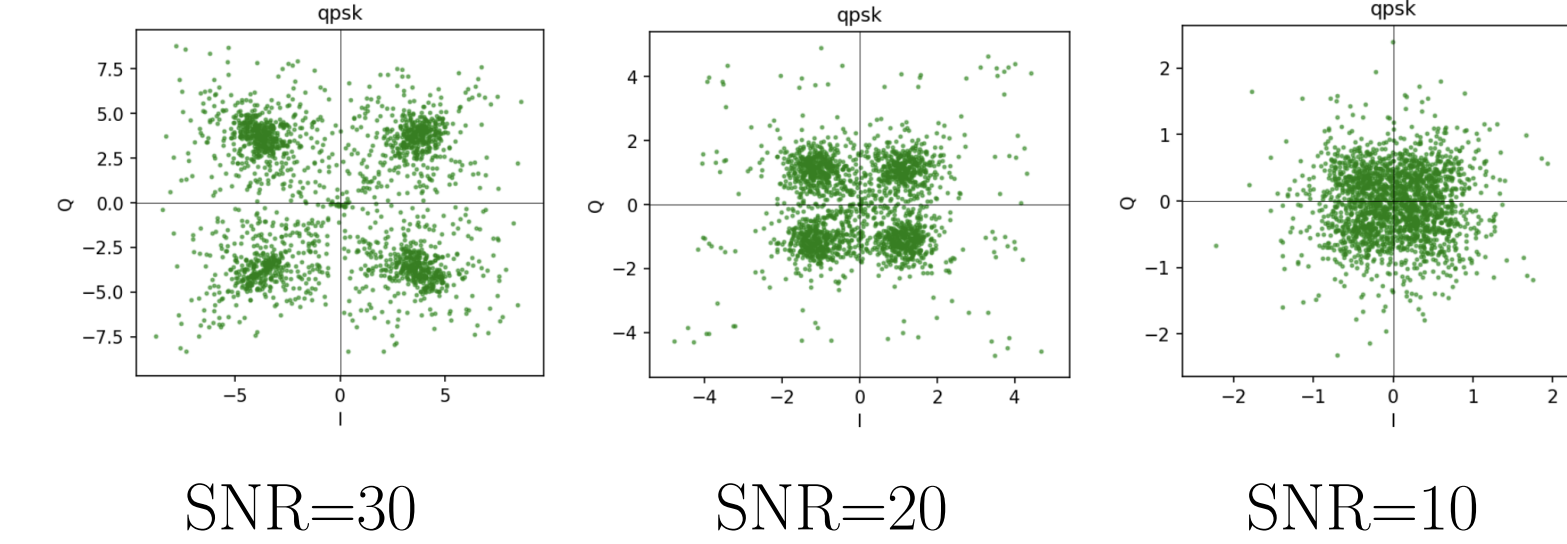
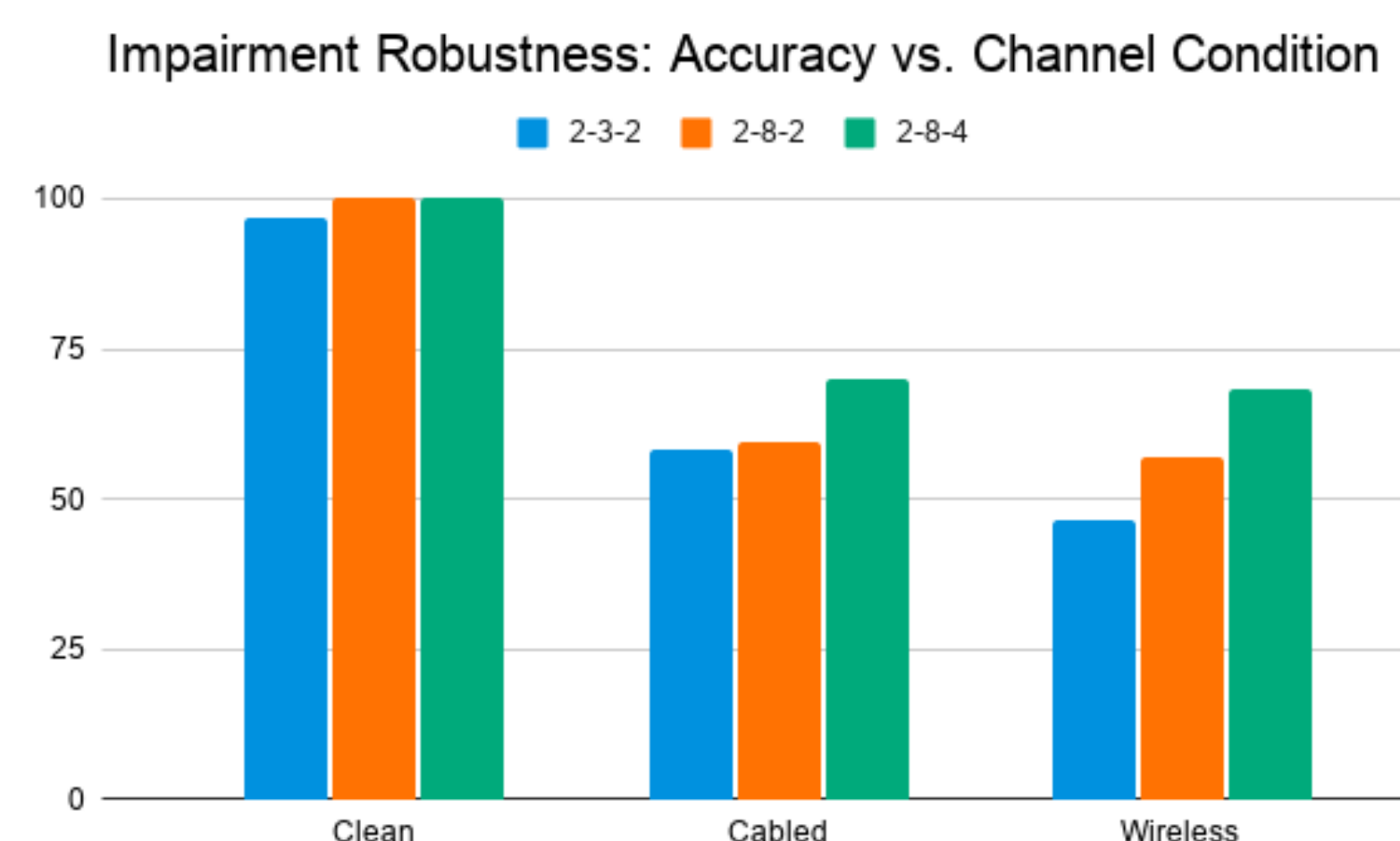
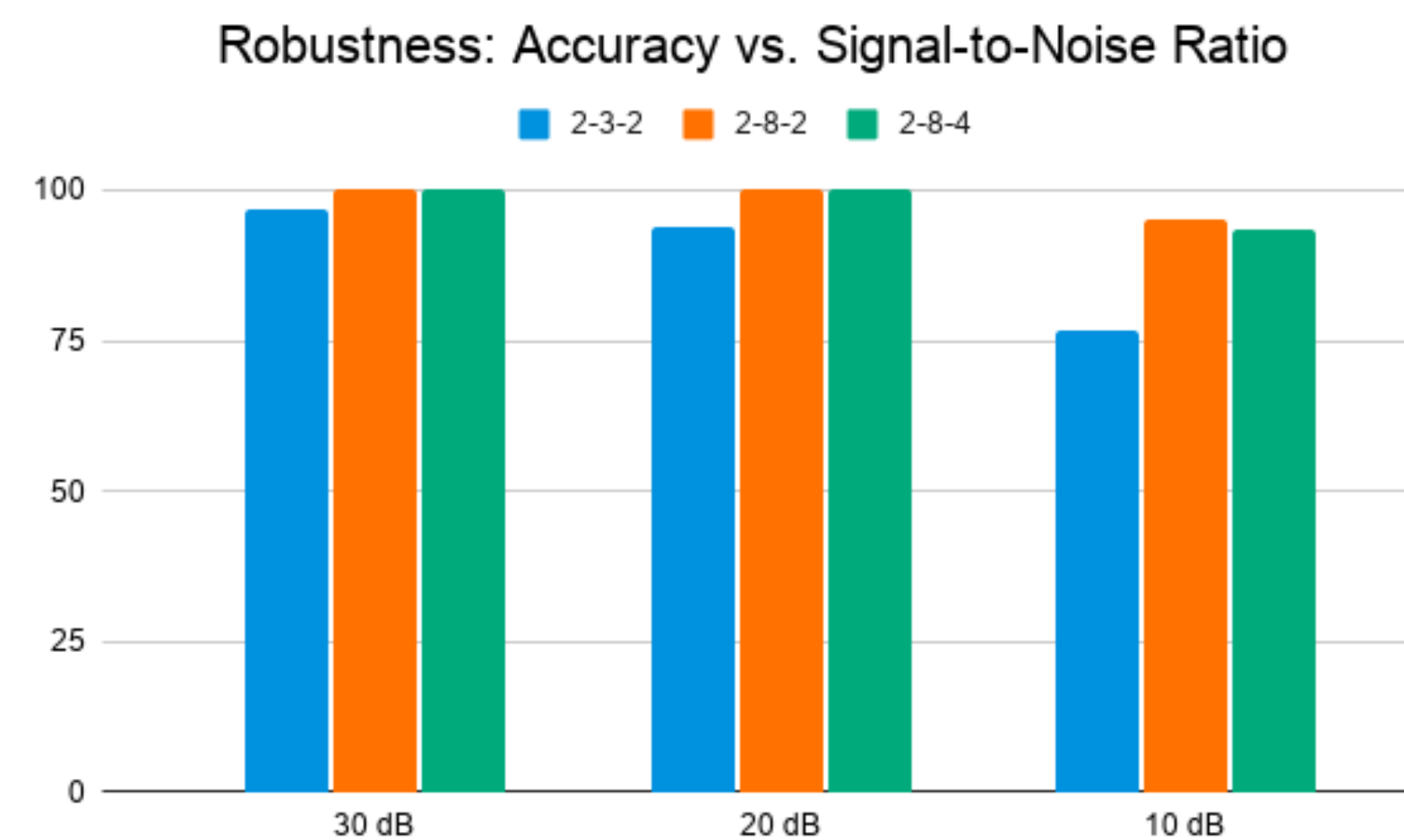


Figure 2: QPSK across SNR and impairment levels



Use Cases

- **Electronic Warfare** — adversaries actively hop frequencies and modulations to evade detection; continuous low-latency AMC is required for interception.
- **Cognitive Radio (5G/6G, WiFi, LANs)** — radios must sense, classify, and adapt to the spectrum in real time; photonic low latency improves response rate in dense RF environments, increasing spectral efficiency.
- **Wideband Signals** — GHz-range bandwidths saturate digital ADCs; photonic processing occurs directly on the analog signal before digitization.
- **Satellite & Airborne** — near-zero marginal power per operation is decisive where energy budgets are hard constraints.

Future Work

- **Physical chip validation** — replace the software Photonic NN with a real fabricated MRR weight bank and validate end-to-end.
- **Analog integrator** — replace with an integrating photodetector, completing the fully analog front-end.
- **FPGA classifier deployment** — hls4ml conversion of the digital classifier onto ZCU216 has been prototyped in Vivado; full hardware-in-the-loop validation is the next step.
- **Impairment-robust training** — augment training data with mixed channel conditions to recover accuracy under fading and multipath.

References & Acknowledgement

- [1] Lederman, J.C. (2025). *Silicon Photonic Systems Applications*. Princeton Ph.D. Thesis.
- [2] TorchSig. github.com/TorchDSP/torchsig
- [3] hls4ml. fastmachinelearning.org/hls4ml

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