ChatGPT

Recent Advances in Low-SNR AMC and Denoising Approaches (2020–2025)

Low-SNR Automatic Modulation Classification (AMC) Performance

- **Abd-Elaziz *et al.*, 2023 – "Deep Learning-Based AMC Using Robust CNN Architecture for CR Networks" (MDPI *Sensors*):** Proposes a novel CNN with parallel asymmetric convolution blocks and skip connections to enhance feature extraction at low SNR. Evaluated on a custom dataset of 9 modulation schemes with AWGN, Rician fading, and clock offset impairments, it achieves **86.1% accuracy at –2 dB SNR**, rising to ~99.8% at 10 dB [1]. This substantially outperformed prior CNN-based models, reliably distinguishing even challenging 16QAM/64QAM in very noisy conditions (overall average accuracy ~81%). Dataset: Simulated + impairments (non-cooperative scenario).

- **Zhang *et al.*, 2023 – "MoE-AMC: Mixture-of-Experts for AMC" (arXiv preprint):** Introduces a **mixture-of-experts** network that routes signals to different sub-models optimized for high vs. low SNR. A Transformer-based expert (LSRM) handles low-SNR signals, while a ResNet-based expert (HSRM) handles high-SNR inputs [2] [3]. A small gating MLP estimates SNR and switches experts accordingly. On the **RML2018.01a** dataset (24 modulations, –20 to 18 dB), MoE-AMC attained **71.76%** average classification accuracy across SNRs – about **10% higher** than prior single-expert CNN or Transformer models [4]. This demonstrates balanced performance: the Transformer branch preserves accuracy below 0 dB while the ResNet branch excels at higher SNR.

- **Rehman *et al.*, 2025 – "DL-AMC: Deep Learning for Automatic Modulation Classification" (arXiv preprint):** Proposes converting raw I/Q waveforms into **eye diagrams** as input to deep CNNs (ResNet-18/50, MobileNet) to boost robustness at low SNR. Trained on a curated set of modulation types with SNR ranging **–20 dB to 30 dB**, the approach achieves **high accuracy even at negative SNRs**, thanks to the noise-resilient eye-diagram representation [5]. For example, at the lowest SNR in tests, the DL-AMC ResNet substantially outperformed earlier deep models – prior approaches like DBN, RNN, LSTM, and CLDNN had only ~10–48% accuracy in the lowest-SNR conditions [6] (near chance-level), whereas the proposed method maintained strong classification performance. *Dataset:* custom-generated signals (multi-SNR) transformed into eye diagrams.

- **Sathyanarayanan *et al.*, 2023 – *IEEE TWC* ("RML22: Realistic Dataset Generation for Wireless Modulation Classification"):** Introduces the **RML22 dataset**, a next-generation public dataset that builds on DeepSig's RadioML by correcting artifacts in RML2016 data and adding more realistic channel effects [7]. RML22 includes a wide range of modulations (likely 24 classes, similar to RML2018) with improved fidelity to over-the-air conditions. The authors' data-centric generation approach yields a benchmark where state-of-the-art models now exceed **99% accuracy at high SNR** [8], underscoring RML22's value for evaluating AMC algorithms. This dataset innovation beyond RadioML 2016/2018 is enabling researchers to validate models under more **realistic multipath and interference** scenarios, bridging the gap between simulation and field performance.

- **Jagannath *et al.*, 2022 – *PHYCOM* (multi-task AMC on SDR testbed):** Demonstrated a real-world validation of deep learning AMC on an **over-the-air SDR platform**. Using a feed-forward CNN-based multi-task classifier (distinguishing both modulation and signal type), they achieved **≈98% accuracy on 7 modulation classes** in a live USRP testbed experiment [9]. This near-perfect accuracy in controlled OTA tests (moderate SNR) highlights that modern DL models can retain high performance outside simulations. It also underscores the importance of heterogeneous training (including impairments and hardware effects) to ensure models generalize to field conditions. *Dataset:* Live OTA captures via USRP; results confirm consistency with simulation benchmarks.

Denoising Front-Ends and Noise-Robust Techniques for AMC

- **An & Lee, 2023 – "Robust AMC in Low SNR" (IEEE *Access*):** Develops a noise-mitigation front-end consisting of a **Thresholded Autoencoder Denoiser (TAD)** and an SNR predictor, integrated before an AMC classifier. The lightweight SNR estimator triggers the denoiser only for low-SNR inputs, avoiding unnecessary processing for high-SNR signals. This design yielded a **~70% relative improvement in low-SNR classification accuracy** (vs. no denoiser) [10]. In other words, the TAD front-end dramatically boosted accuracy in heavy noise scenarios (e.g. from ~30% to ~51% on a very low SNR set). The overall model (TAD + CNN) achieved robust performance down to ~–10 dB SNR, illustrating the effectiveness of learned denoising. *Datasets:* Evaluated on RadioML 2016/2018 variants; the approach improved low-SNR accuracy across these benchmarks.

- **Faysal *et al.*, 2025 – "DenoMAE: A Multimodal Denoising Autoencoder for Modulation Signals" (arXiv):** Presents a **denoising masked autoencoder** that treats *noise as an additional modality* during self-supervised pre-training. DenoMAE is pre-trained to reconstruct clean I/Q signals and their constellation diagrams from masked, noisy inputs (leveraging both raw waveform and constellation image domains). After fine-tuning for classification, this approach reached **83.5% accuracy** on a 10-class modulation task using only 1,000 labeled samples (with 10,000 unlabeled pre-training samples) [11]. Crucially, it maintains strong generalization at very low SNR: e.g. **77.5% accuracy at –10 dB** [12] [13], which is a ~22% improvement over the same model without MAE pre-training. DenoMAE also outperformed prior denoising methods (e.g. CNN-AMC, DL-GRF) by **24–33%** in low-SNR regimes [13]. *Dataset:* Simulated multi-SNR signals (10 modulations); comparisons show DenoMAE's efficacy in noise-intensive environments and even on SNR levels lower than seen in training (extrapolation).

- **Suman & Qu, 2023 – "Lightweight AMC via Dual-Path Residual Shrinkage Network" (MDPI *Electronics*):** Proposes an efficient CNN-LSTM architecture with an internal **learnable denoising mechanism**. The model uses **deep residual shrinkage blocks** with *garrote thresholding* to adaptively suppress noise in feature maps. Despite only ~27k parameters, it achieved **≈62% average accuracy** on the 24-class RML2018.01a dataset (–20 to 18 dB) [14], rivaling larger models. An ablation showed the garrote-based denoiser yields slightly higher low-SNR accuracy than standard soft-thresholding – about **2.2% better in the –4 to +6 dB SNR range** [15]. The network's maximum accuracy at high SNR reaches ~97–98%, and it degrades gracefully as SNR drops [16] [17]. This demonstrates that clever threshold-based denoising **within** the model can boost noise robustness with minimal complexity overhead (garrote added ~0.6% FLOPs). *Datasets:* Evaluated on RML2016/2018; the method targets edge devices, showing that denoising boosts accuracy without heavy computation.

Sources: The above findings are drawn from recent open-access publications and preprints, including arXiv papers, IEEE journals, and MDPI journals, with relevant metrics and details cited for each. Researchers have also released code and datasets (e.g. RML22 on GitHub, DenoMAE on GitHub) alongside these works, aiding reproducibility and further experimentation [18] [11]. Each study highlights a trend toward improving AMC performance below 0 dB SNR – whether by novel neural architectures or by introducing explicit denoising – and validates those improvements either on realistic synthetic data or through over-the-air tests. These contributions collectively advance the reliability of modulation classification in interference-heavy, low-SNR environments.

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