
Detect, Extract, Recognize: Wideband RF Signal Detection and Modulation Recognition with Over-the-Air Validation

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Abstract

Radio dynamic zones (RDZs) and other dynamic spectrum-sharing regimes require sensing systems that can detect and characterize previously unknown emitters. While automatic modulation recognition (AMR) is an important component of RF spectrum sensing capability, nearly all AMR methods assume the signal of interest has already been detected, isolated, and handed to the classifier which is specifically not a valid assumption for RDZs. In this paper, We present an integrated RF analysis framework that combines signal detection and modulation recognition, with over-the-air evaluation using software-defined radios. A YOLOv11 detector localizes signals in time-frequency spectrograms and estimates their temporal and spectral boundaries. These regions are mapped to the corresponding complex I/Q data, where individual signals are extracted and classified using a lightweight one-dimensional attention-based model. Using TorchSig-generated data with 57 waveform classes over 0–30 dB SNR, the detector achieves 99.2% mAP@0.5, while the classifier achieves 62.1% fine-grained accuracy and approximately 92% modulation-family accuracy. Over-the-air evaluation shows fine-grained accuracy increasing from 23.7% at 2 dB to 65.2% at 25 dB, with family-level accuracy reaching 98.0%. Overall, the proposed framework provides a unified pathway from RF signal detection to modula-

tion recognition and supports more complete automated RF spectrum analysis.

1. Introduction

Effective use of increasingly crowded RF spectrum requires sensing systems that can provide more than a simple indication of signal presence. In practical wideband environments, a sensing system should also determine what type of signal is present and where that activity occurs in time and frequency. These capabilities are particularly important in dynamic spectrum-sharing environments and radio dynamic zones (RDZs) (U.S. National Science Foundation, 2022; Maeng et al., 2022; nra, 2025), where spectrum access decisions depend on an accurate understanding of ongoing RF activity. Automatic modulation recognition (AMR) (Nandi & Azzouz, 1998; Zhang et al., 2022; Peng et al., 2022) provides waveform-level characterization by identifying the modulation type or modulation family of an over-the-air (OTA) transmission. This information can support signal identification, receiver configuration, interference analysis, and downstream demodulation, making AMR an important intermediate stage between signal detection and higher-level receiver processing. AMR has been widely studied using both conventional signal-processing techniques and, more recently, deep-learning approaches (Xu et al., 2026; Qu et al., 2025) under different signal-to-noise ratios (SNRs), channel conditions, and receiver impairments (Zhang et al., 2022; Boegner et al., 2022a; Tang et al., 2026). However, most AMR frameworks assume that the signal of interest has already been detected and isolated before being provided to the classifier (Xiao et al., 2022). In a wideband RF environment, multiple signals may occupy different time-frequency regions, while their duration, bandwidth, and carrier location

may not be known in advance (Boegner et al., 2022a; Xing et al., 2024). Therefore, practical modulation recognition requires signal activity detection and extraction to be integrated with the classification process.

Traditional AMR approaches rely on likelihood methods (Sills, 1999; Wei & Mendel, 2000a; Panagiotou et al., 2000; Lay & Polydoros, 1994; 1995; Chugg et al., 1995; Hong & Ho, 2002) or handcrafted features such as higher-order statistics, spectral characteristics, and cyclostationary properties (Wei & Mendel, 2000b; Xu et al., 2011). Deep-learning methods instead learn modulation-dependent representations directly from received I/Q samples (Bhavana & Sabat, 2025; Wang et al., 2025; Zhou et al., 2020; Biswas et al., 2024; Hicks et al., 2025; 2024). CNNs (O’Shea et al., 2016), recurrent models (Rajendran et al., 2018; Ansari et al., 2025; Dong et al., 2025), efficient CNN architectures (Huynh-The et al., 2020), and attention/Transformer-based methods (Cai et al., 2022; Zheng et al., 2022) have all been explored for AMR. TorchSig has also enabled large-scale synthetic RF data generation (Boegner et al., 2022a). West et al. (West et al., 2021) studied joint signal detection, time-frequency localization, and recognition, while Boegner et al. (Boegner et al., 2022b) introduced a TorchSig-based model for multi-signal detection and recognition. Cascaded detection and classification, including YOLO-based RF detection, have also been investigated (Vagollari et al., 2023; Xing et al., 2024; Hsue & Soliman, 1990). Hauser et al. (Hauser et al., 2017) further showed that detection and isolation errors can degrade downstream raw-IQ classification. Despite these advances, directly connecting time-frequency detection with event-level I/Q extraction and fine-grained modulation recognition remains limited in practical spectrum-analysis workflows.

Another consideration in the development of RF machine-learning models is the dependence on synthetically generated data (Boegner et al., 2022a;b). Synthetic RF data provide accurate signal labels and allow parameters such as modulation type, SNR, bandwidth, carrier frequency, channel conditions, and receiver impairments to be systematically controlled during training (O’Shea & West, 2016). This makes synthetic data particularly useful for training large modulation-recognition models across a broad range of operating conditions. However, physically transmitted and received signals can contain additional effects introduced by RF hardware and the propagation environment (Woo et al., 2024; Xu et al., 2010). Therefore, evaluation using signals transmitted and received through software-defined radios (SDRs) provides an important assessment of whether a model trained using synthetic data can maintain its recognition capability under practical RF conditions.

In this work we present an integrated wideband sensing pipeline for RF activity detection, signal extraction, and

modulation recognition, and evaluate it on both synthetic and over-the-air (OTA) data. The contributions of this paper are as follows:

- An integrated wideband sensing pipeline that connects spectrogram-domain signal localization to event-level complex I/Q extraction and fine-grained modulation recognition generating per emitter descriptors such as center frequency, occupied bandwidth and time and waveform class.
- We present a class agnostic detection model. For this a YOLOv11-based object-detection model is applied to time-frequency spectrograms to identify multiple RF activities and estimate their temporal and spectral boundaries. We show that a binary RF-activity detector yields more complete and higher-confidence detections at low SNR than a modulation-aware models.
- The detected signals are filtered allowing the associated complex I/Q samples to be extracted for downstream modulation recognition. For classification, we employ a lightweight one-dimensional attention-based architecture that uses cross-covariance attention and local patch interaction to learn modulation-dependent characteristics directly from I/Q samples. The classifier is trained using TorchSig-generated synthetic data (Nguyen et al., 2025; Boegner et al., 2022a;b) covering 57 modulation and waveform classes over an SNR range of 0–30 dB, with additional channel and hardware impairments including fading, I/Q imbalance, carrier phase variations, pass-band distortion, clock drift, and quantization.
- An over-the-air evaluation of a synthetically trained recognition model on signals physically transmitted and received through SDR hardware, without retraining or fine-tuning on measured data.

2. DATASET

Two task-specific RF data configurations were constructed using the TorchSig framework (Boegner et al., 2022a) for wideband RF activity detection and modulation recognition. For both tasks, the generated signals covered an SNR range of 0–30 dB and included channel- and hardware-related impairments such as fading, carrier phase offset, carrier phase noise, and I/Q imbalance. For RF activity detection, multiple RF signals were placed at different temporal and spectral locations within each observation. The corresponding complex I/Q data were converted to time-frequency representations using the short-time Fourier transform (STFT), and the resulting magnitude spectrograms were used as detector inputs. The known

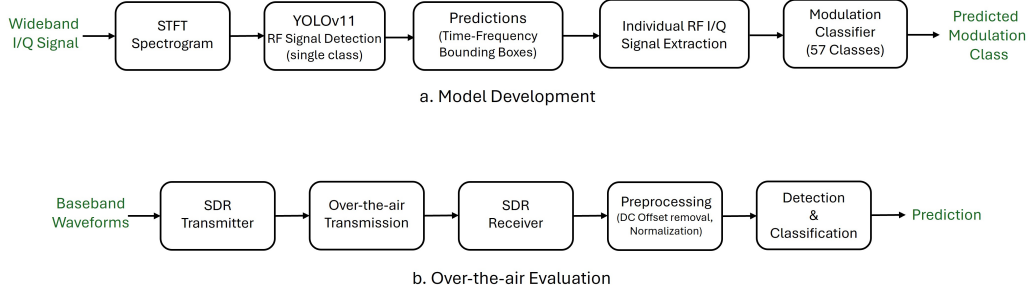


Figure 1. Overall framework for RF signal detection and modulation recognition: (a) model development with spectrogram-based detection, I/Q extraction, and classification, and (b) SDR-based over-the-air evaluation.

temporal and spectral support of each signal was mapped to bounding-box annotations, with all modulation and waveform types assigned to a single RF-activity class. The detection dataset contained 250,000 training samples, with 10,000 samples each for validation and testing.

For modulation recognition, each example consisted of 4096 complex I/Q samples generated at a sampling rate of 10 MHz. A total of 57 modulation and waveform classes were considered and grouped into eight broader families: ASK, Analog, Chirp, FSK, OFDM, PAM, PSK, and QAM. Training examples were generated online during optimization, resulting in approximately 50 million independently generated signal realizations over the complete training procedure. Separate fixed validation and test sets were used for repeatable evaluation, with 2,000 samples per class, resulting in 114,000 samples in each split.

For testing OTA using the GRC setup with SDRs, we generate test signals of length 262144 that are different from the training data, at a sampling rate of 1 MS/s and transmit different modulations repeatedly for a given duration of time. The continuous stream of data is captured using the SDR and a fixed window of the samples is taken for classification.

3. Proposed Method

Our proposed approach consists of two stages: model development followed by over-the-air (OTA) evaluation, as illustrated in Fig. 1. Synthetic RF signals are used to train a YOLOv11-based RF signal detector and a lightweight one-dimensional attention-based modulation-recognition model. The OTA stage evaluates modulation recognition using signals transmitted and received through SDR hardware.

3.1. Model Development

3.1.1. ACTIVITY DETECTION

Wideband RF activity detection is performed in the time-frequency domain, as illustrated in Fig. 1. The complex I/Q observations described in Section II are converted to time-frequency spectrograms using the short-time Fourier transform (STFT), and a YOLOv11-based object detector is used to estimate the temporal and spectral span of individual RF signals. Although YOLOv11 can jointly perform localization and multiclass prediction, modulation recognition is intentionally excluded from this stage. The time-frequency spectrogram preserves the energy distribution of a signal but does not explicitly retain the complex phase information available in the original I/Q representation. Consequently, modulation classes within a single family can be difficult to distinguish. In multiclass experiments, modulation-specific prediction reduced class confidence due to poor classification performance resulting in increased missed detections. Therefore, all waveform types are assigned to a single RF-activity class, and YOLOv11 is used only for signal presence and detection. The predicted bounding boxes provide estimates of signal duration, center frequency, and occupied bandwidth.

3.1.2. I/Q SIGNAL EXTRACTION

The time-frequency regions predicted by YOLOv11 are mapped back to the original complex I/Q observation to extract individual RF events. The temporal extent of each bounding box is used to crop the corresponding signal interval, while its spectral location and width provide estimates of the center frequency and occupied bandwidth. A small temporal margin is included around each detected interval to reduce signal truncation. The cropped signal is subsequently translated to baseband using the estimated center frequency and low-pass filtered according to the detected bandwidth. A Butterworth filter with a small spectral margin and zero-phase filtering is used to suppress out-of-

band components while avoiding additional phase distortion. As shown in Fig. 1, this stage converts each time-frequency detection into an individually isolated complex I/Q event for subsequent signal-level analysis.

3.1.3. MODULATION RECOGNITION

Fine-grained modulation recognition is performed using a lightweight one-dimensional attention-based architecture following the RF adaptation of XCiT in (Boegner et al., 2022a). The classifier is trained independently from the YOLOv11 based RF activity detector and operates directly on complex I/Q data, preserving both amplitude and phase information. Each input consists of 4096 complex samples represented as separate in-phase and quadrature channels. The inputs are normalized using their root-mean-square power before being provided to the network.

The model uses a one-dimensional convolutional patch embedding with kernel size 8 and stride 4 to obtain a 192-dimensional feature representation. The resulting sequence is processed by 12 XCiT-style blocks with four attention heads. Each block combines cross-covariance attention with local patch interaction implemented using depthwise one-dimensional convolutions. The final feature sequence is globally averaged and passed to a linear layer for classification across the 57 modulation and waveform classes. The classifier is optimized using AdamW with label smoothing, gradient clipping, learning-rate warm-up, and cosine learning-rate decay. Distributed multi-GPU and mixed-precision training are used to support the large-scale online training, and the final model is selected based on performance on the fixed validation set.

3.2. Over-the-Air

The OTA evaluation was conducted using two independent radio front-ends of a single Ettus USRP X310 SDR shown in Fig. 2. The signal was transmitted through channel A (TX/RX) and received through channel B (TX/RX). Both channels operated at a carrier frequency of 3.2 GHz and a sampling rate of 1 MS/s. An external Rubidium frequency standard provided a 10 MHz reference and pulse-per-second (PPS) signal to maintain frequency and timing coherence. The operating signal to noise ratio (SNR) was controlled by varying the transmit and receive gains. For each setting, the noise power was first measured with the transmitter (TX) off, followed by measurement of the signal-plus-noise power using a known reference signal. The effective SNR was then obtained from these measurements. This procedure was repeated over different gain settings to evaluate the classifier across a range of SNR conditions. Double ridge horn antennas were used placed on a horizontal platform at a distance of 0.5 m apart.

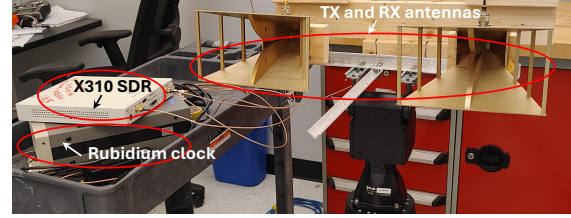


Figure 2. Hardware setup for modulation classification (at the edge) OTA using SDR.

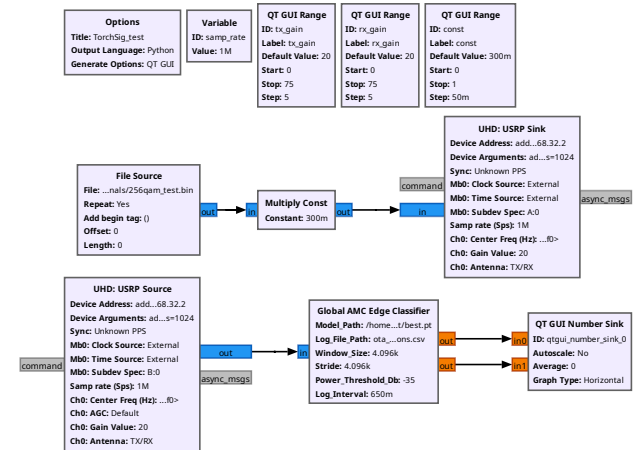


Figure 3. Flowgraph in the GRC for modulation classification using the trained classifier.

3.2.1. OTA MODULATION RECOGNITION

The transmit and receive processing was implemented in a single GNU Radio Companion (GRC) flowgraph. At the TX, a file source repeatedly streams a stored complex-baseband test signal, which is scaled to the desired transmit level and sent to the USRP sink on channel A. At the receiver (RX), the USRP source on channel B feeds the received signal to a custom embedded-Python classification block. The flowgraph in GRC is shown in Fig. 3. The block divides the signal into non-overlapping 4096-sample windows, applies the normalization, and passes each window to the trained classifier. For each window, the classifier outputs probabilities for the modulation classes, from which the most likely modulation and corresponding signal family are identified along with their confidence values. The results, including timestamps, modulation and family indices, confidence scores, and window power, are recorded. The test signals are generated independently from the training data, ensuring that the observed performance reflects the physical RF channel rather than synthetic impairments. The classifications are obtained at different SNR levels by changing the SDR gain at the TX and RX.

4. Results and Discussion

This section presents the performance of the proposed framework for wideband RF activity detection, I/Q signal extraction, and modulation recognition, together with over-the-air validation using physically transmitted and received RF signals.

4.0.1. RF DETECTION AND CLASSIFICATION

The RF signal detection stage achieved high detection accuracy over the evaluated SNR range. The single-class YOLOv11 detector achieved a 99.2% mAP@0.5 on the held-out test set spanning 0–30 dB SNR. Representative detection outputs for the 57-class and single-class formulations at 5 and 15 dB are shown in Fig. 4. At 5 dB, the 57-class detector produces several low-confidence predictions and fails to detect multiple signal instances, whereas the single-class detector identifies a larger number of the same signals with higher confidence. At 15 dB, the performance gap is reduced, although the single-class formulation still provides more complete and consistent time-frequency detection. These results demonstrate that separating RF signal detection from modulation identification improves detection robustness,

The predicted time-frequency regions are subsequently mapped back to the original wideband complex I/Q observation to recover the corresponding signal instances. A representative example is shown in Fig. 5, where three simultaneously occurring RF signals are localized and individu-

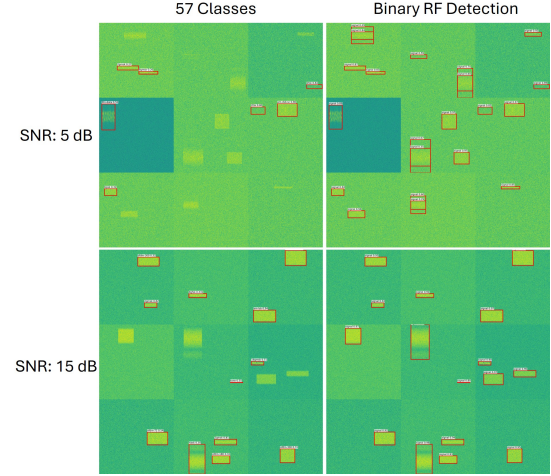


Figure 4. Representative RF signal detection results for the multi-class and single-class YOLOv11 detectors at 5 and 15 dB SNR.

ally isolated using the estimated temporal boundaries, center frequencies, and occupied bandwidths. Each extracted segment is translated to baseband and filtered according to its predicted bandwidth to suppress adjacent spectral components. The filter responses and resulting baseband spectrograms in Fig. 5 show that the detected signals are successfully separated from the wideband observation and re-centered near zero frequency while preserving their characteristic time-frequency structure.

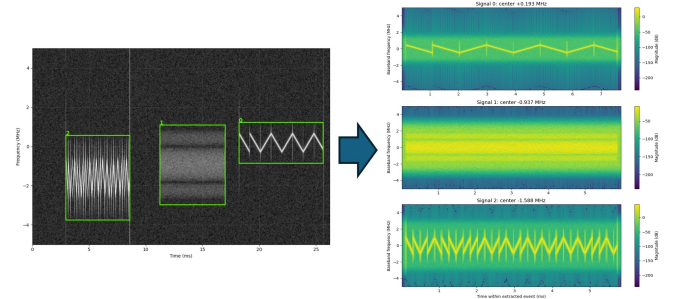


Figure 5. Representative I/Q signal extraction from a wideband observation using the detected time-frequency regions.

The modulation-recognition stage was evaluated independently using the fixed test set of 114,000 unseen signals spanning the 57 waveform classes. The overall top-1 accuracy across the 0–30 dB SNR range was 62.1%. Figure 6 shows the variation in classification accuracy with SNR under both nominal and impaired signal conditions. In the presence of the modeled channel and hardware impairments, accuracy increases from 30.6% at 0 dB to 81.3% at 30 dB, while the corresponding performance without these additional impairments increases from 33.9% to 87.1%.

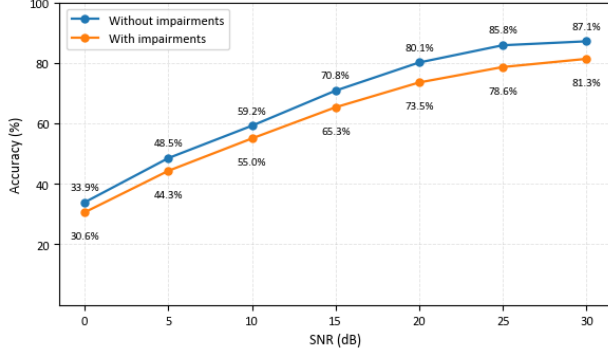


Figure 6. Modulation classification accuracy across SNR levels with and without additional channel and impairments.

To further examine the structure of the remaining errors, the 57 waveform classes were grouped into eight modulation families, and the resulting normalized confusion matrix is presented in Fig. 7. The classifier achieved an overall family-level accuracy of approximately 92.0%, considerably higher than the fine-grained 57-class accuracy. Strong discrimination is observed for families such as FSK and chirp-based waveforms, while relatively greater confusion remains for some analog and PAM signals. The difference between class-level and family-level performance suggests that a substantial portion of the residual errors occurs between closely related waveform variants within the same modulation family.

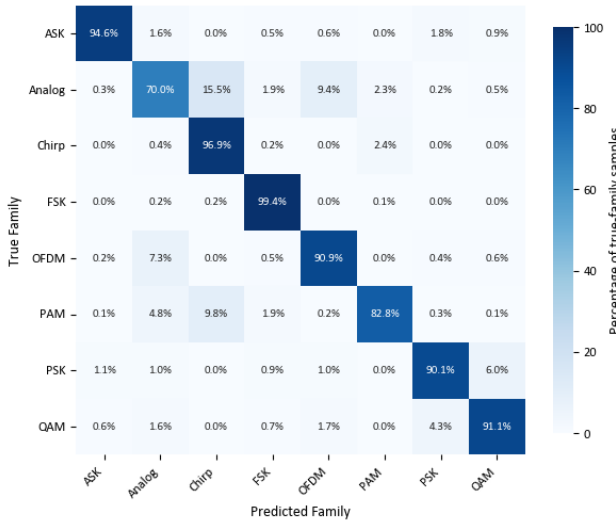


Figure 7. Confusion matrix showing modulation classification performance across the eight modulation families

4.0.2. OVER-THE-AIR EVALUATION

The modulation-recognition model was further evaluated using RF signals physically transmitted and received through the SDR-based OTA setup. The evaluation included 48 digital modulation classes at measured SNR levels of 2, 10, 15, 25, and 30 dB. A 2 dB operating point was used for the lowest-SNR condition because an exact 0 dB level could not be reliably established in the hardware setup. As shown in Fig. 8, recognition performance improves substantially with increasing SNR. Fine-grained classification accuracy increases from 23.7% at 2 dB to 65.2% at 25 dB, while the corresponding family-level accuracy increases from 75.0% to 98.0%. At 30 dB, comparable performance is maintained, with 64.5% fine-grained accuracy and 97.4% family-level accuracy. The observed OTA performance despite the change from a 10 MHz synthetic sampling rate to a 1 MHz SDR sampling rate is consistent with the classifier relying on frequency characteristics normalized with respect to the sampling rate rather than on an absolute bandwidth. The consistently higher family-level performance indicates that the synthetically trained classifier generalizes well to physically acquired RF signals at the broader modulation-family level, while distinguishing closely related modulation types remains more challenging under OTA conditions.

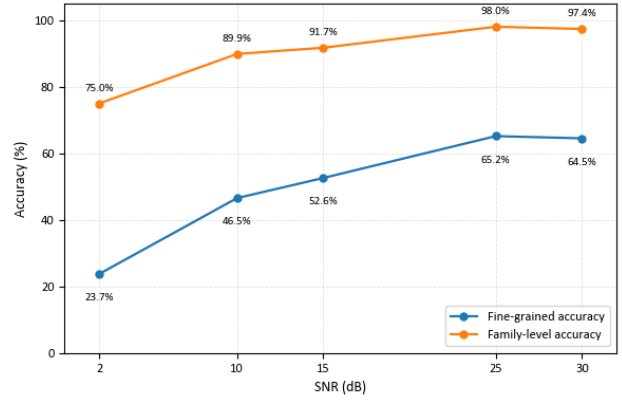


Figure 8. Confusion matrix showing modulation classification performance across the eight modulation families

5. CONCLUSION

This work presents a multi-stage framework that combines spectrogram-based RF signal detection with complex I/Q-based modulation recognition for automated RF spectrum analysis. The proposed approach enables detection of individual RF signals from complex observations while retaining the phase and amplitude information required for fine-grained waveform recognition. The experimental re-

sults indicate that the detection stage can reliably identify signal regions over a broad SNR range, while the modulation-recognition model provides strong discrimination at the broader modulation-family level. The high family-level performance further suggests that a hierarchical recognition strategy may be beneficial, where an initial classifier first identifies the modulation family and a subsequent specialized classifier performs fine-grained discrimination among waveform variants within that family. The OTA evaluation also demonstrates the applicability of the learned recognition model to physically transmitted and received RF signals. Future work will focus on testing developed models on more realistic outdoor environments with independent radios, longer links, and evaluation under more diverse channel, interference, and hardware conditions.

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References

- An experimental test-bed for investigating spectrum sharing strategies between passive and active users at a prototype national radio dynamic zone (nrdz). 2025. VERIFY authors, venue, and pages – IEEE Xplore doc. 10906834.
- Ansari, Sam, Mahmoud, Soliman, Majzoub, Sohaib, Al-majali, Eqab, Jarndal, Anwar, and Bonny, Talal. A novel lstm architecture for automatic modulation recognition: Comparative analysis with conventional machine learning and rnn-based approaches. *IEEE Access*, 13:72526–72543, 2025. doi: 10.1109/ACCESS.2025.3564032.
- Bhavana, Bandaru and Sabat, Samrat L. A low-complexity deep learning model for modulation classification and detection of radar signals. *IEEE Transactions on Aerospace and Electronic Systems*, 61(2):2548–2556, 2025. doi: 10.1109/TAES.2024.3475328.
- Biswas, Sabyasachi, Ayna, Cemre Omer, and Gurbuz, Ali Cafer. Plfnets: Interpretable complex-valued parameterized learnable filters for computationally efficient rf classification. *IEEE Transactions on Radar Systems*, 2: 1102–1111, 2024. doi: 10.1109/TRS.2024.3486183.
- Boegner, Luke, Gulati, Manbir, Vanhoy, Garrett, Vallance, Phillip, Comar, Bradley, Kokalj-Filipovic, Silvija, Lennon, Craig, and Miller, Robert D. Large scale radio frequency signal classification, 2022a. URL <https://arxiv.org/abs/2207.09918>.
- Boegner, Luke, Vanhoy, Garrett, Vallance, Phillip, Gulati, Manbir, Feitzinger, Dresden, Comar, Bradley, and Miller, Robert D. Large scale radio frequency wideband signal detection recognition, 2022b. URL <https://arxiv.org/abs/2211.10335>.
- Cai, Jingjing, Gan, Fengming, Cao, Xianghai, and Liu, Wei. Signal modulation classification based on the transformer network. *IEEE Transactions on Cognitive Communications and Networking*, 8(3):1348–1357, 2022. doi: 10.1109/TCCN.2022.3176640.
- Chugg, Keith M, Long, Chu-Sieng, and Polydoros, Andreas. Combined likelihood power estimation and multiple hypothesis modulation classification. In *Conference Record of The Twenty-Ninth Asilomar Conference on Signals, Systems and Computers*, volume 2, pp. 1137–1141. IEEE, 1995.
- Dong, Ying, Zhai, Ruotong, Zhong, Yufeng, Rong, Zhen, Wang, Yong, and Wang, Chunyue. A novel distributed solution for automatic modulation classification based on federated learning and modified lstm. *IEEE Transactions on Vehicular Technology*, 74(8):12290–12302, 2025. doi: 10.1109/TVT.2025.3551765.
- Hauser, Steven C., Headley, William C., and Michaels, Alan J. Signal detection effects on deep neural networks utilizing raw iq for modulation classification. In *MILCOM 2017 - 2017 IEEE Military Communications Conference (MILCOM)*, pp. 121–127, 2017. doi: 10.1109/MILCOM.2017.8170853.
- Hicks, Bruce, Biswas, Sabyasachi, Dahal, Ajaya, Gonzalez, Victor, and Gurbuz, Ali C. Automatic waveform recognition from complex rf data with filter-based deep learning. In *NAECON 2024 - IEEE National Aerospace and Electronics Conference*, pp. 168–172, 2024. doi: 10.1109/NAECON61878.2024.10670353.
- Hicks, Bruce, Biswas, Sabyasachi, and Gurbuz, Ali Cafer. Learnable gaussian filter-based automatic rf waveform modulation recognition. In *2025 IEEE International Radar Conference (RADAR)*, pp. 1–6, 2025. doi: 10.1109/RADAR52380.2025.11032063.
- Hong, Liang and Ho, KC. Antenna array likelihood modulation classifier for bpsk and qpsk signals. In *MILCOM 2002. Proceedings*, volume 1, pp. 647–651. IEEE, 2002.
- Hsue, S-Z and Soliman, Samir S. Automatic modulation classification using zero crossing. In *IEE Proceedings F (Radar and Signal Processing)*, volume 137, pp. 459–464. IET, 1990.
- Huynh-The, Thien, Hua, Cam-Hao, Pham, Quoc-Viet, and Kim, Dong-Seong. Mcnet: An efficient cnn architecture

- for robust automatic modulation classification. *IEEE Communications Letters*, 24(4):811–815, 2020. doi: 10.1109/LCOMM.2020.2968030.
- Lay, Norman E and Polydoros, Andreas. Per-survivor processing for channel acquisition, data detection and modulation classification. In *Proceedings of 1994 28th Asilomar Conference on Signals, Systems and Computers*, volume 2, pp. 1169–1173. IEEE, 1994.
- Lay, Norman E and Polydoros, Andreas. Modulation classification of signals in unknown isi environments. In *Proceedings of MILCOM'95*, volume 1, pp. 170–174. IEEE, 1995.
- Maeng, S. J., Güvenç, İ., Sichiitiu, M. L., Floyd, B., Dutta, R., Zajkowski, T., Ozdemir, O., and Mushi, M. National radio dynamic zone concept with autonomous aerial and ground spectrum sensors. In *IEEE International Conference on Communications (ICC) Workshops*, 2022. VERIFY exact venue/pages; also arXiv:2203.09014.
- Nandi, A.K. and Azzouz, E.E. Algorithms for automatic modulation recognition of communication signals. *IEEE Transactions on Communications*, 46(4):431–436, 1998. doi: 10.1109/26.664294.
- Nguyen, Quang Minh, Nguyen, Lam M., and Das, Subhro. Correlated attention in transformers for multivariate time series. In *ICASSP 2025 - 2025 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 1–5, 2025. doi: 10.1109/ICASSP49660.2025.10889540.
- O'Shea, Tim and West, Nathan E. Radio machine learning dataset generation with gnu radio. 2016. URL <https://api.semanticscholar.org/CorpusID:114654356>.
- O'Shea, Timothy J., Corgan, Johnathan, and Clancy, T. Charles. Convolutional radio modulation recognition networks. In Jayne, Chrisina and Iliadis, Lazaros (eds.), *Engineering Applications of Neural Networks*, pp. 213–226, Cham, 2016. Springer International Publishing. ISBN 978-3-319-44188-7.
- Panagiotou, Prokopios, Anastasopoulos, Achilleas, and Polydoros, A. Likelihood ratio tests for modulation classification. In *MILCOM 2000 Proceedings. 21st Century Military Communications. Architectures and Technologies for Information Superiority (Cat. No. 00CH37155)*, volume 2, pp. 670–674. IEEE, 2000.
- Peng, Shengliang, Sun, Shujun, and Yao, Yu-Dong. A survey of modulation classification using deep learning: Signal representation and data preprocessing. *IEEE Transactions on Neural Networks and Learning Systems*, 33(12):7020–7038, 2022. doi: 10.1109/TNNLS.2021.3085433.
- Qu, Yunpeng, Lu, Zhilin, Zeng, Rui, Wang, Jintao, and Wang, Jian. Enhancing automatic modulation recognition through robust global feature extraction. *IEEE Transactions on Vehicular Technology*, 74(3):4192–4207, 2025. doi: 10.1109/TVT.2024.3486079.
- Rajendran, Sreeraj, Meert, Wannes, Giustiniano, Domenico, Lenders, Vincent, and Pollin, Sofie. Deep learning models for wireless signal classification with distributed low-cost spectrum sensors. *IEEE Transactions on Cognitive Communications and Networking*, 4(3):433–445, 2018. doi: 10.1109/TCCN.2018.2835460.
- Sills, James A. Maximum-likelihood modulation classification for psk/qam. In *MILCOM 1999. IEEE Military Communications. Conference Proceedings (Cat. No. 99CH36341)*, volume 1, pp. 217–220. IEEE, 1999.
- Tang, Zixi, Luo, Chunbo, Yin, Yihao, and Luo, Yang. Acmr: An automatic composite-modulation recognition dataset and baselines. *IEEE Transactions on Vehicular Technology*, 75(7):13225–13235, 2026. doi: 10.1109/TVT.2026.3656598.
- U.S. National Science Foundation. Spectrum innovation initiative: National radio dynamic zones (sii-nrdz), 2022. Program Solicitation NSF 22-579.
- Vagollari, Adela, Hirschbeck, Martin, and Gerstacker, Wolfgang. An end-to-end deep learning framework for wideband signal recognition. *IEEE Access*, 11:52899–52922, 2023. doi: 10.1109/ACCESS.2023.3280454.
- Wang, Xiang, Zhao, Yurui, and Huang, Zhitao. A survey of deep transfer learning in automatic modulation classification. *IEEE Transactions on Cognitive Communications and Networking*, 11(3):1357–1381, 2025. doi: 10.1109/TCCN.2025.3558027.
- Wei, Wen and Mendel, Jerry M. Maximum-likelihood classification for digital amplitude-phase modulations. *IEEE transactions on Communications*, 48(2):189–193, 2000a.
- Wei, Wen and Mendel, J.M. Maximum-likelihood classification for digital amplitude-phase modulations. *IEEE Transactions on Communications*, 48(2):189–193, 2000b. doi: 10.1109/26.823550.
- West, Nathan, O'Shea, Timothy, and Roy, Tamoghna. A wideband signal recognition dataset. In *2021 IEEE 22nd International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, pp. 6–10, 2021. doi: 10.1109/SPAWC51858.2021.9593265.

Woo, Jongseok, Jung, Kuchul, and Mukhopadhyay, Saibal. Efficient hardware design of dnn for rf signal modulation recognition employing ternary weights. *IEEE Access*, 12:80165–80175, 2024. doi: 10.1109/ACCESS.2024.3409180.

Xiao, Wenshi, Luo, Zhongqiang, and Hu, Qian. A review of research on signal modulation recognition based on deep learning. *Electronics*, 11(17), 2022. ISSN 2079-9292. doi: 10.3390/electronics11172764. URL <https://www.mdpi.com/2079-9292/11/17/2764>.

Xing, Huijun, Zhang, Xuhui, Chang, Shuo, Ren, Jinke, Zhang, Zixun, Xu, Jie, and Cui, Shuguang. Joint signal detection and automatic modulation classification via deep learning. *IEEE Transactions on Wireless Communications*, 23(11):17129–17142, 2024. doi: 10.1109/TWC.2024.3450972.

Xu, Dongwei, Hou, Jiaye, Song, Fuxing, Chen, Zhuangzhi, Zheng, Shilian, Xuan, Qi, Lin, Yun, and Yang, Xiaoniu. Amee: Automatic modulation open set recognition through deep metric learning with embedding enhancement. *IEEE Transactions on Reliability*, 75:203–217, 2026. doi: 10.1109/TR.2025.3634616.

Xu, Jefferson L., Su, Wei, and Zhou, MengChu. Software-defined radio equipped with rapid modulation recognition. *IEEE Transactions on Vehicular Technology*, 59(4):1659–1667, 2010. doi: 10.1109/TVT.2010.2041805.

Xu, Jefferson L., Su, Wei, and Zhou, Mengchu. Likelihood-ratio approaches to automatic modulation classification. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 41(4): 455–469, 2011. doi: 10.1109/TSMCC.2010.2076347.

Zhang, Fuxin, Luo, Chunbo, Xu, Jialang, Luo, Yang, and Zheng, Fu-Chun. Deep learning based automatic modulation recognition: Models, datasets, and challenges. *Digital Signal Processing*, 129:103650, 2022. ISSN 1051-2004. doi: <https://doi.org/10.1016/j.dsp.2022.103650>. URL <https://www.sciencedirect.com/science/article/pii/S1051200422002676>.

Zheng, Qinghe, Zhao, Penghui, Wang, Hongjun, Elhanashi, Abdussalam, and Saponara, Sergio. Fine-grained modulation classification using multi-scale radio transformer with dual-channel representation. *IEEE Communications Letters*, 26(6):1298–1302, 2022. doi: 10.1109/LCOMM.2022.3145647.

Zhou, Ruolin, Liu, Fugang, and Gravelle, Christopher W. Deep learning for modulation recognition: A survey with a demonstration. *IEEE Access*, 8:67366–67376, 2020. doi: 10.1109/ACCESS.2020.2986330.