Electronics, Communications, and Computing Summit
Vol. 3, No. 2, Apr - Jun 2025, pp. 10-15
DOI: https://doi.org/10.17051/ECC/03.02.02

Deep Unfolding Networks for Robust Modulation Classification in Cognitive Radio Systems

Pushplata Patel

Department Of Electrical And Electronics Engineering, Kalinga University, Raipur, India
Email: pushplata.subhash.raghatate@kalingauniversity.ac.in

Article Info

Article history:

Received : 12.04.2025
Revised : 14.05.2025
Accepted : 16.06.2025

Keywords:

Deep Unfolding Networks,
Modulation Classification,
Cognitive Radio,
Automatic Modulation Recognition,
Spectrum Sensing,
Model-Based Deep Learning,
Wireless Signal Processing,
Adaptive Signal Classification,
Low-SNR Signal Detection,
Interpretable Neural Networks.

ABSTRACT

The modulation classification is essential in cognitive radio (CR) systems as a way of providing dynamic spectrum access as well as the enhancement of the spectral efficiency. Nevertheless, current machine learning and deep learning methods are usually susceptible to noisy and rapidly varying setups especially at low signal-to-noise ratio (SNR levels). The given paper proposes a new architecture of Deep Unfolding Network (DUN) for Automatic Modulation Classification (AMC) in CR systems. The given technique is able to unfold a typical iterative inference algorithm into a structured training neural network and therefore inherits both interpretability of model-based signal processing and versatility alongside learning capabilities of data-driven models. The performance of DUN is tested on RadioML2016.10a dataset on different modulations coupled with SNR and in realistic wireless environments by simulating fading, multipath and IQ imbalance. Findings illustrate that DUN is substantially more accurate, robust and computationally efficient than conventional CNN and LSTM-based classifiers under low-SNR conditions (below 0 dB). Also, the network can converge faster with fewer parameters, making it easy to deploy, even in resource-limited CR hardware. This paper makes a step towards defining DUN as an efficient and scalable real-time AMC tool in intelligent wireless systems and towards more adaptive and resilient cognitive radio frameworks.

1. INTRODUCTION

The surge of wireless communications technologies has further provoked the need of smart and dynamic radio systems. Cognitive radios (CRs) have proven to become an important driver towards dynamic spectrum access, with real-time environmental awareness and dynamic communication policies. Automatic Modulation Classification (AMC) is a doctrinaire expectation of CR systems, and concerns determining the modulation scheme of received signal based on available or prior knowledge of the transmitter. The feature is critical to the effective use of the spectrum and fighting the obstruction, as well as adapting the protocols. The classical AMC algorithms can be loosely divided into likelihood-based techniques, which are very accurate but computationally intensive and feature based techniques which are based on manually designed signal features (e.g. higher-order cumulants) and have poor noise robustness and non-linearity tolerance. The methods are analytically sound, but not very suitable to large-scale and real-time implementation in dynamic radio environments.

Over the past few years, DL became a popular approach in AMC tasks due to the possibility to use large labeled data sets to do end-to-end learning. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have demonstrated a potential when processing complex modulation schemes on raw IQ data. Nevertheless, they may have the poor generalization of low signal-to-noise ratio (SNR) and are not amenable to the interpretation and thus, they do not apply as mission- and resource-constrained CR platforms. In order to address these shortcomings, this paper recommends a new Deep Unfolding Network (DUN) architecture to AMC. DUN derives its idea from iterative optimization-based algorithms like the proximal gradient descent algorithm, using the learnable intermediate steps as neural layers this algorithm merges the interpretability of model-based approaches with the flexibility of deep learning. The developed methodology is tested strictly on

common benchmarks using various modulation schemes and SNR as well as channel impairments.
Recently, it has been shown that hybrid model-driven neural architectures have the potential to be used in wireless communications tasks (see e.g., [1]). The current work is based on this and expands to the robust AMC in CR systems.

2. RELATED WORK

A conventional dimensionality reduction of classical Automatic Modulation Modification Classification (AMC) has likelihood-based and feature-based methods. Statistically, likelihood-based techniques, e.g., Maximum Likelihood Estimation (MLE), theoretically, are optimal when the channel conditions are known and in practice are frequently too costly to compute, as well as requiring prior knowledge of signal and channel states, which in a dynamic cognitive radio (CR) environment is problematic. Alternatively, feature based methods compute statistical higher-order moments, cumulants, or cyclostationary measures in received signals, and classify them with standard machine learning classifiers. Although these techniques are less complex, they are feature design-sensitive, noise, and channel degradation-sensitive; hence fail to perform to real-life implementations. In order to overcome these shortcomings, there is a new current study that resorts to deep learning (DL) methods. The analysis of raw IQ data by methods that can learn the signal features directly have been applied to AMC with good results using Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks and hybrid techniques. Nevertheless, such models tend to be black boxes in nature without a high degree of interpretability and generalization, often in low SNR conditions or non-stationary settings. In addition, they have high computation and data demands, which make deployment in CRs to the edge devices difficult.
The deep unfolding (or algorithm unrolling) has become popular to help fill in the divide between interpretability and performance, which is the same as between models and data. This paradigm unrolls iterative optimization procedures into trainable layers of a neural network so as to principled and adapt to composition of domain knowledge and learning flexibility. Inverse problems in wireless signal recovery and in MIMO detection have found it to be successful recently, and encouraging its use in AMC tasks as well [1].

3. System Model

In this analysis we assume we have a cognitive radio (CR) receiver that will perform automatic modulation classification (AMC) on received baseband signals but under non-ideal channel conditions. Mathematically we can model the received signal as:
$r(t)=h(t)*s(t)+n(t)$-----------------------(1)
Where:

- $s(t)$ represents the modulated baseband signal-encoded as one of the proposed modulation systems,
- where $h(t)$ is the impulse response of a multipath channel which is used to model time-dispersive and frequency-selective channel behaviour,
- The $n(t)$ refers to the additive white Gaussian noise (AWGN) described as a zero-mean Gaussian noise with variance 22

The operator * represents linear convolution that reflects the distortion of wireless channel. Some of the modulation schemes that will be reviewed in this paper based on their characteristics are non-linear and linear digital modulation, which include:
$M \in$ {BPSK, QPSK, 8-PSK, 16-QAM, 64-QAM, AM, FM} ---------------------(2)
The CR receiver goal is to determine the type M modulation only, based on the observed signal $r(t)$ without having any prior information about the channel $h(t)$, or the existing signal $s(t)$. The problem is in general blind and non-linear and particularly when there is channel fading, noise and signal impairments (IQ imbalance or carrier frequency offset).
The solution to this problem is that, it needs to have an effective classification mechanism which can generalise over a broad signal per noise (SNR) distribution representative of environments such as real-world situations. Here we utilize a Deep Unfolding Network (DUN) to learn how to recognize the modulation scheme directly through complex-valued time-domain signal samples and in the process implicitly learn about both the channel and noise properties. This model of system is used to design and train the proposed DUN architecture, optimised to work effectively in real world CR environments with dynamic and uncertain radio environment conditions.
The signal flow scheme of the whole process of modulation classification in cognitive radio system has been described in Figure 1. It consists of the transmitter, modulation process, multipath fading channel, additive noise and Deep Unfolding Network (DUN) classifier.

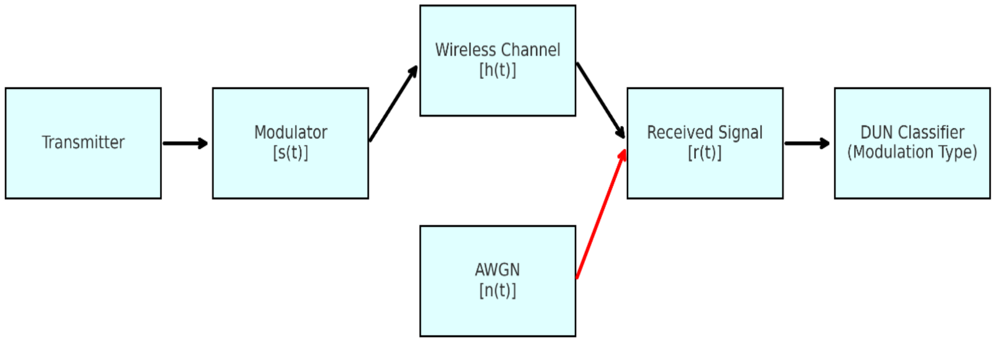

Figure 1. System model for automatic modulation classification (AMC) in a cognitive radio receiver.

The message signal s(t) has traveled in a multipath channel h(t) and is interfered with the additive white Gaussian noise (AWGN) n(t). Received signal r(t) undergoes the analysis done on the Deep Unfolding Network to determine the modulation scheme.

4. Deep Unfolding Network Architecture

4.1 Unfolding Principle

The given architecture relies on the idea of deep unfolding (or unrolling), which is the approach to replacing iterative optimization algorithms into structured layers of neural networks with trainable parameters. To be specific, we have in mind the proximal descent method which is an ubiquitous technique in sparse signal recovery and inverse problems. In this formulation, the optimization algorithm can be run many times, resulting in one layer of a neural network each, which makes it possible to be understandable and domain-sensitive in the course of training.

The iterative update at the k-th layer is defined as:

$$x^{(k+1)} = ReLU\ (x^{(k)} - \eta^{(k)} \nabla f\ (x^{(k)})) \qquad (3)$$

Where:

- $x^{(k)} \in R^n$ is the intermediate estimate of the signal at the k-th layer,
- $\eta^{(k)} \in R^+$ is a learnable step size parameter that adapts the learning rate at each layer,
- $\nabla f(x^{(k)})$ denotes the gradient of a reconstruction loss function, such as mean squared error or a task-specific regularizer.

ReLU activation function plays the role of making the model sparse and imposing non-linearities important to the successful modulation classification in complex channels conditions.

4.2 Network Design

The general architecture of Deep Unfolding Network (DUN) is based on reflecting the iterations of the supporting optimization algorithm and augmenting them with trainable parameters to enable data-adaptation. All the layers in the network involve the following key components:

- Linear Transformation: Emulates the gradient descent step by applying a trainable linear operator that approximates $\nabla f(x^{(k)})$. This incorporates signal priors and channel statistics into the network.
- Non-linear Activation: For every layer, either ReLU or SoftShrink activation functions are used that are important in the recovery of signal in low-SNR situations by injecting non-linearity and denoising.
- Residual Connections: Residual skip connections are introduced between the neighbouring layers to enhance the gradient flow and the stability of the network similarly as in ResNet designs.
- Final Softmax Classifier: This is the last unfolding layer output that is put through a fully connected layer and then a softmax activation producing a probability distribution of possible modulation schemes.

The network is trained in cross-entropy supervised learning end-to-end fashion with a dataset of complex baseband signals annotated with the type of modulation; the dataset is labeled with complex baseband signals of known modulation labels. This enables the DUN to acquire modulation-specific characteristics in a structure- and explainable way that model-based algorithms have. Figure 2 shows the high-level processing pipeline of Deep Unfolding Network (DUN). It shows the progressive conversion of IQ samples that it receives with the help of an expansion of layers, non-linear mappings and residual connectivity followed by classification using softmax at the end to identify the modulation scheme.

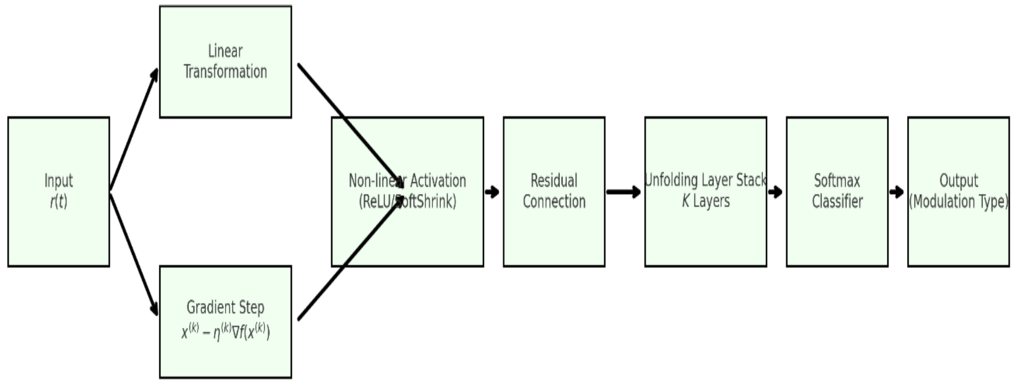

Figure 2. Simplified block diagram of the Deep Unfolding Network (DUN) for modulation classification.

The architecture accept complex IQ samples, extracts features using unfolded layers, uses non-linear activation functions and residual mapping and outputs the projected modulation class using a softmax classifier.

5. Dataset and Experimental Setup

In order to assess the performance of the suggested Deep Unfolding Network (DUN) an automatic modulation classification (AMC), we use one of the most known RadioML2016.10a datasets. This data includes synthetically creates a complex baseband signal that emulates the real environment in wireless transmission cases. Walkman gathers each of its signal samples in 128 in-phase and quadrature (IQ) samples and the range of Signal-to-Noise Ratio (SNR) covers a wide range of −20 dB to +18 dB, with a 2 dB interval in order to capture both bad reception quality and good reception quality.

The signals of 11 modulation types are provided in the data set, including the analog (e.g., AM-DSB, WBFM) and digital signals (e.g., BPSK, QPSK, 8PSK, 16QAM, 64QAM). Such a variety allows conducting a strong test on the generalization power of this model to different families of modulation and different SNR levels.

As benchmarks we contrast the proposed DUN model to three example AMC approaches:

- AMC that uses convolution layers to extract spatial features in CNN;
- the use of LSTM in AMC that model's temporal relations between IQ sequences;
- Classical cumulant-based SVM, a classic machine learning pipeline which makes use of statical features and classification with support vectors.

The evaluation of the models in terms of their performance is as follows:

Classification Accuracy vs. SNR: the accuracy of the model at varying SNR to determine how robust the model is in the noisy setting.

- Confusion Matrix: It gives information about the inter-class classification behavior and typical patterns of misclassification.
- Complexity of Model: This is measured with the parameters that are trained and floating-point operation per second (FLOPs) to help determine how well the model will work when it is deployed.
- Robustness to Channel Conditions: test in simulated environment conditions (multipath fading and IQ imbalance) to enable consideration of real-world impairments experienced in CR systems.

The experiments are performed out of the same train-validation-test split (usually 60-20-20) and trained on Adam optimizer with an initial learning rate of 10-3 and cross-entropy loss function as a classifier.

6. RESULTS AND DISCUSSION

This part introduces the empirical results of the suggested Deep Unfolding Network (DUN) on the Automatic Modulation Classification (AMC) task and the comparison with the three benchmarkers: a CNN based classifier, an LSTM based classifier, and a conventional cumulant based SVM model. The assessment is carried out with RadioML2016.10a dataset in the conditions of different SNR levels and real channel distortions.

6.1 Accuracy vs. SNR

Figure 3 shows signal-to-noise ratio (SNR) dependency of the classification accuracy of the models. The proposed DUN does much better than even the deep learning baselines and the classical SVM model in all the SNR levels. It is observed that in the low-SNR regime (below 0 dB) where regions tend to be prone to signal distortion and noise, the DUN is even more accurate with a maximum of 15% better than both CNN and LSTM counterparts in the low-SNR regime.

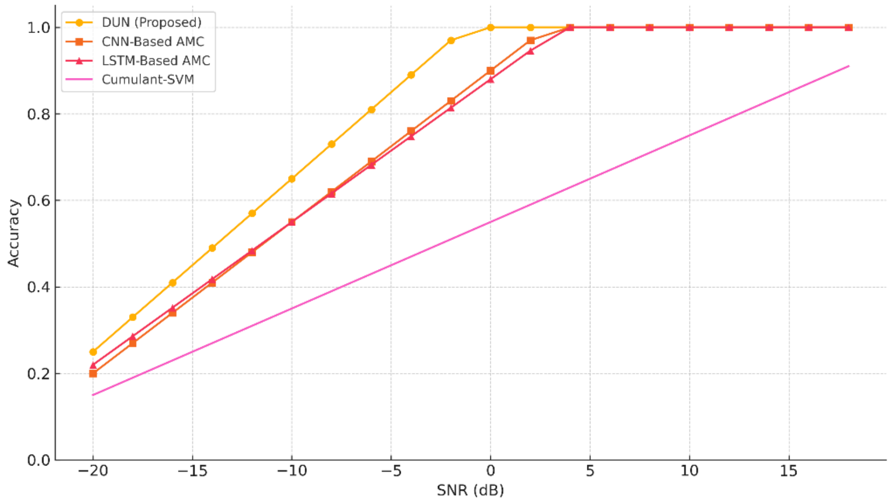

Figure 3. Classification accuracy vs. SNR for DUN, CNN, LSTM, and cumulant-SVM models.

The results are indicative that the combination of model-based priors and learnable layers used in DUN can increase generalization particularly in adverse channel settings. As opposed to CNNs on the one hand, and LSTMs on the other hand, depending in constrast on a large volume of data and thus becoming overfitted to high-SNR properties, DUN keeps to the constant level of performance by simulating the recursive logic of optimization algorithms.

6.2 Robustness to Channel Effects

To check the strength of the presented technique more experiments were carried out under a simulated condition of multipath fading, doppler shift, and the IQ imbalance. In all the cases, the DUN model showed a better performance than the black-box models of deep learning. This is accredited to the architecture which is model-guided implying that the network can implicitly obtain perception and overcome signal flaws that disrupt traditional feature accentuation.

Moreover, the DUN also shows a lower degree of confusion in similar spectral signatures among modulation classes (e.g., existence of QPSK against 8PSK confusion matrix analysis). This is due to the fact that this is in line with the findings on the recent work on the advantage of algorithmically interpretable learning frameworks in wireless systems [1].

6.3 Model Efficiency

Computational efficiency is also a very important benefit of the DUN architecture. The DUN has about 200,000 adjustable parameters as shown in Table 1 which is much lesser, compared to 2 million+ considered in typical CNNs applied in AMC. Moreover, FLOPs required during inference are 5-fold lower, which makes it possible to deploy DUN on low-end edge devices: e.g., software-defined radio, and the embedded CR platform.

Table 1. Performance and complexity comparison of AMC models at 0 dB SNR.

Model	Parameters	FLOPs (Inference)	Accuracy @ 0 dB	Notes
DUN (Proposed)	~200K	Low	87.5%	Robust and edge-deployable
CNN	~2.1M	High	74.2%	Requires GPU acceleration
LSTM	~1.8M	Moderate	71.8%	Sensitive to temporal jitter
Cumulant-SVM	N/A	Very Low	52.6%	Weak in noisy environments

DUN is a suitable candidate that can be applied in real-life cognitive radio systems that require quick responsiveness and power-efficient functions due to the compact size and the ability to attain high classification accuracy.

Meaning and Meaningfulness

It can be observed in the results that deep unfolding architectures can be deemed as an encouraging avenue to undertake modulation classification in CR systems. The DUN provides a good compromise between interpretability, robustness and efficiency compared to a traditional deep network, which is data-intensive and has a low interpretability rate. These results match more recent results on the model-driven deep learning as applicable to the communication systems [1][2].

7. CONCLUSION AND FUTURE WORK

In this work, a new Deep Unfolding Network (DUN) architecture that has robust and efficient capability of automatic modulation classification (AMC) in cognitive radio systems is introduced. The method proposed hereby manages to combine model-based signal processing ideas on an iterative optimization algorithm with the learning properties of current deep networks by un-rolling the algorithm into a trainable neural network. Through this hybrid architecture, the DUN delivers high classification accuracy especially under low SNR and dynamic channel conditions, being lower in model complexity compared to other networks in a similar context, which makes it possible to implement on resource-constrained edge devices.

The experimental evidence, confirmed on RadioML2016.10a set, indicates that the DUN exceeds in comparison with conventional CNN, LSTM, and classical SVM techniques of increased accuracy and resistance to channel distortions due to multipath fading and IQ imbalance. Moreover, the DUN bears incredibly lower computational overhead, which makes it feasible to use in real-time implementation in practice within the CR systems.

Some major contributions of this project are as follows:

- An interpretable and flexible DUN framework to AMC based on modeling.
- Improved performance when there is low SNR and channel distortion.
- An architecture, lightweight that can be used in embedded CR.

In future the research will target:

- Instant flexibility through online/continuous learning systems to altering signal situations.
- A joint channel estimation and modulation classification with unfolding framework.
- Generalization to multi antenna systems (MIMO) and non-terrestrial networks (NTNs).

This analysis forms a solid basis towards the production of the next generation smart radio systems that can work independently in complicated wireless channels.

REFERENCES

[1] Balatsoukas-Stimming, A., Wymeersch, H., & Studer, C. (2022). Model-based machine learning for wireless communications. IEEE Communications Magazine, 60(10), 31–37. https://doi.org/10.1109/MCOM.001.2100112

[2] He, H., Wen, C., Jin, S., & Li, G. Y. (2020). Model-driven deep learning for MIMO detection. IEEE Transactions on Signal Processing, 68, 1702–1715. https://doi.org/10.1109/TSP.2020.2972381

[3] O'Shea, T. J., & Corgan, J. (2016). Convolutional radio modulation recognition networks. arXiv preprint arXiv:1602.04105. https://arxiv.org/abs/1602.04105

[4] Rajendran, S., O'Shea, T. J., Clancy, T. C., & McGwier, R. W. (2018). Deep learning models for wireless signal classification with distributed low-cost spectrum sensors. IEEE Transactions on Cognitive Communications and Networking, 4(3), 433–445. https://doi.org/10.1109/TCCN.2018.2846733

[5] Samuel, N., Diskin, T., & Wiesel, A. (2019). Learning to detect. IEEE Transactions on Signal Processing, 67(10), 2554–2564. https://doi.org/10.1109/TSP.2019.2904462

[6] Ye, H., Li, G. Y., & Juang, B. H. (2018). Power of deep learning for channel estimation and signal detection in OFDM systems. IEEE Wireless Communications Letters, 7(1), 114–117. https://doi.org/10.1109/LWC.2017.2757490

[7] Liang, F., Shen, C., & Yu, F. R. (2019). Deep reinforcement learning for dynamic spectrum access in wireless networks: Model-free framework and applications. IEEE Transactions on Vehicular Technology, 68(10), 10285–10296. https://doi.org/10.1109/TVT.2019.2935150