Efficient and Robust AI-Based Automatic Modulation Classification

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Outline

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Automatic Modulation Classification (AMC)

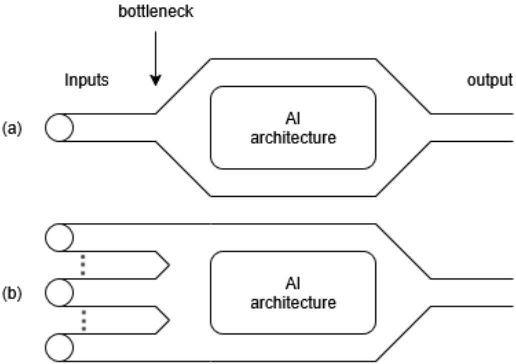
- Automatic Modulation Classification (AMC) is key for **cognitive radios and spectrum monitoring** (civilian and military)
- Real-world applications demand fast, robust, and **lightweight solutions**
- **AMC** dates back to the early days of telecommunications, initially driven by military and surveillance requirements
- **Evolution of methodologies**:
  - *Classical/statistical approaches*: decision trees, likelihood-based methods (e.g., CDF)
  - *Feature-based ML*: spectral and cyclostationary features combined with algorithms like KNN, SVM, GA
  - *Modern deep learning*: CNNs, LSTMs, Transformers
- **This research explores how input transformations and scales before an 'AI' model affect AMC accuracy**

Outline

Signal Surface Augmentation

1. **Signal expansion:** Instead of feeding the raw signal directly into the network, SSA first decomposes the signal into multiple components or scales.
2. **Meaningful decomposition:** Well-designed decompositions generate informative and interpretable scales that better capture the underlying signal structure.
3. **Enhanced feature extraction:** The expanded signal representation provides more opportunities for the network to extract relevant features.
4. **Improved performance:** This richer input representation leads to improved classification accuracy.
5. **Regularization effect:** Despite the increased representation capacity, SSA improves performance without causing overfitting.

Signal Surface Augmentation (Simplified illustration)



Mitigating data overdispersion via prior signal decomposition: (**a**) classical bottleneck situation; (**b**) flow opening through decomposition

What SSA Is Not

1. **Multi-scale network architectures** SSA does not rely on in-network scaling mechanisms (e.g., varying kernel sizes or wavelet encoders) but performs meaningful signal decomposition *before* the network.
2. **Multimodal fusion** SSA does not combine different data types; it decomposes a single data modality into multiple informative components.
3. **Parameter inflation in the input layer** SSA is not a simple increase in trainable parameters, as improved performance is achieved even with comparable or fewer parameters.
4. **Data augmentation** SSA does not generate additional training samples but enhances feature visibility through signal decomposition.

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1 Application: Automatic Modulation Classification (AMC)

2 Signal Surface Augmentation

3 Three Examples of SSA
- Dyadic Down-sampling
- Time-Interleaved ADCs
- Alternative LSTM Model

Dyadic Down-sampling – Concept

- Iterative down-sampling by a factor of 2 ($x_d[n] = x[2n]$).
- Captures information at multiple resolutions.
- Low complexity: $\mathcal{O}(N)$.

Dummy vector:

$$\begin{bmatrix} 0 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 \end{bmatrix} \tag{1}$$

The first scale (with a **dyadic factor of 2**) using the dyadic sub-sampling scheme would be:

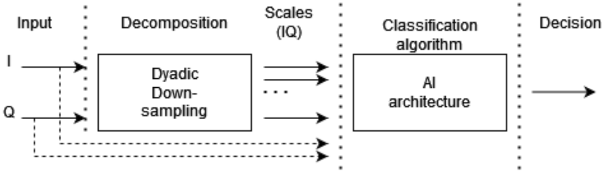
$$\begin{bmatrix} 0 & 2 & 4 & 6 & 8 \end{bmatrix} \tag{2}$$

Second scale (with a dyadic factor of 4) down-converted by retaining only one out of every four samples:

$$\begin{bmatrix} 0 & 4 & 8 \end{bmatrix} \tag{3}$$

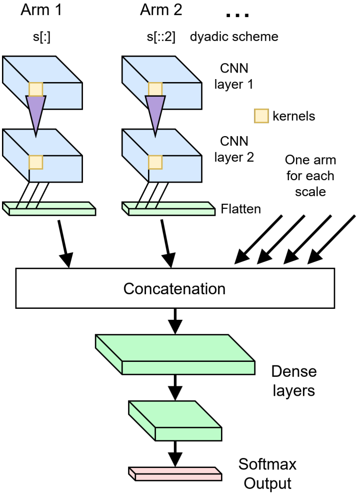
CNN Fusion Architecture

- Dyadic down-sampling provides a multiscale representation of each signal
- All scales are processed simultaneously by a **CNN fusion** architecture
- Separate CNN **arms** per scale and the original signal
- Features are flattened and fused via dense layers
- Enables explainability (**XAI**) and modular design



Global overview of the CNN layer fusion architecture

CNN Fusion Architecture



Global overview of the CNN layer fusion architecture

Architecture parameters

Parameter	Value	Remarks
CNN kernels layer 1	40	activation="ReLU"
Dropout	50%	
CNN kernels layer 2	10	activation="ReLU"
Dropout	50%	
Dense nodes layer 1	a)256 b)128	activation="ReLU"
Aggregation layer nodes	8	activation='softmax'

The whole architecture (six arms and dense layers) is quite **small** with one-twelfth the size of VGG16 (138.4×106).

Further analysis, investigates the effects of convolutional **kernel sizes**, **dense layer** configurations, and **signal lengths** (sample counts) through **hyperparameter optimization**.

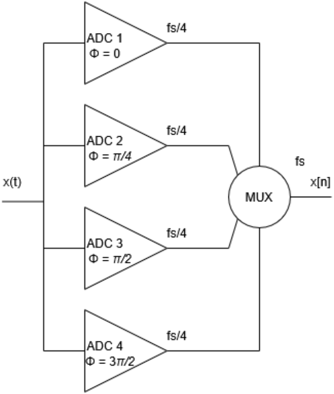
Classification Accuracy Comparison

Effect of the scales validation accuracy (%)

No	Scale	Accuracy
1	IQ, O'Shea's DB & model	51.8
2	IQ, O'Shea's DB, eq. SNR & model	74.5
3	HOC, No AI	82.0
4	IQ with the model from Table 14-b)	86.2
5	Dyadic scale df=2	76.0
6	Dyadic scale df=4	71.0
7	Dyadic scale df=8	35.0
8	Dyadic scale df=16	37.0
9	Dyadic scale df=32	25.5
10	Original IQ + Dyadic scale df=2	88.5
11	Original IQ + Dyadic scales df=2 and df=4	88.8
12	**Original IQ + all scales**	89.0

Time-Interleaved ADCs – Context

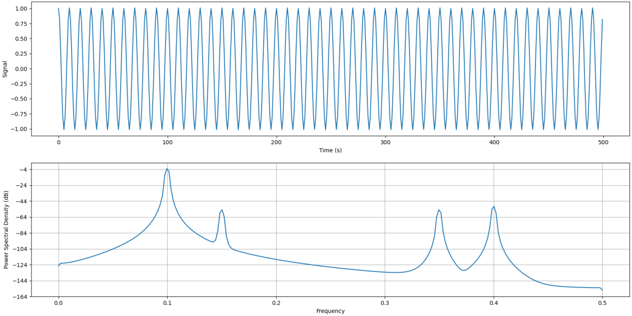
- Used to boost sampling rate for wideband receivers
- Composed of **M parallel ADC cores**
- Can introduce **mismatches**: gain, offset, timing skew



$$y_I[n] = g_{I,m} \cdot x_I(n + \delta_{I,m}) + o_{I,m},$$
$$y_Q[n] = g_{Q,m} \cdot x_Q(n + \delta_{Q,m}) + o_{Q,m},$$

ADC Mismatches – Challenges

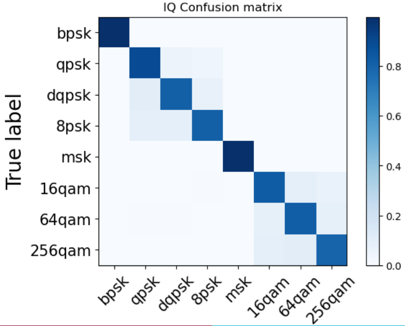
- Spur generation, phase shifts, SNR reduction
- Especially harmful for AMC, as it can lead to signal distortion
- We simulate mismatches on existing IQ data for evaluation
- Needs to be done in passband (around carrier)

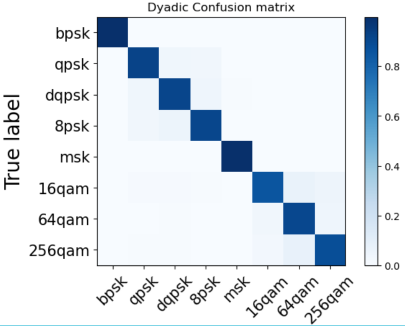


$f_{noise} = \pm f_{in} + \frac{k}{M} f_s$ with $k = 1, 2, 3, ...$
$f_{in}, -f_{in} + \frac{f_s}{4}, f_{in} + \frac{f_s}{4}, -f_{in} + \frac{f_s}{2} f_s = 1, f_c = 0, M = 4, f_{in} = 0.1$ (normalized frequencies)

Results — Dyadic Sampling Performance

- **Consistent accuracy improvement** across all SNR levels:
  - **+4.8%** average absolute gain.
  - Up to **+6.0%** with 4096-sample inputs.
  - Peak gain of **+8.3%** at 4.5 dB SNR.
- Improvements remain significant under mismatch conditions (absolute gains between **4.1% and 6.6%**).
- Low computational overhead due to adaptive dyadic filtering.





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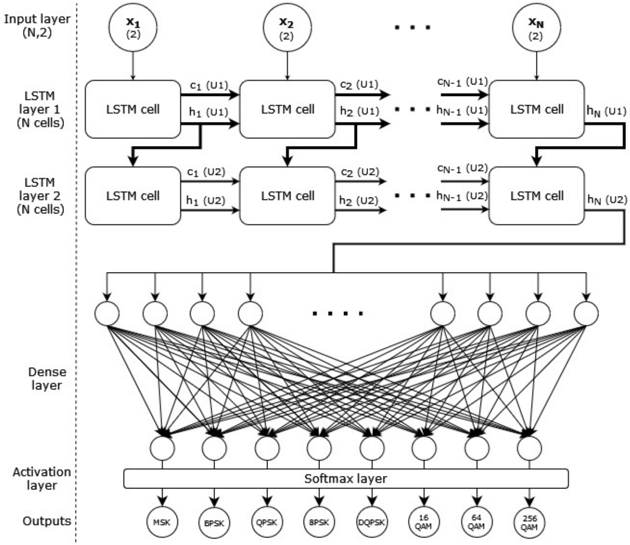
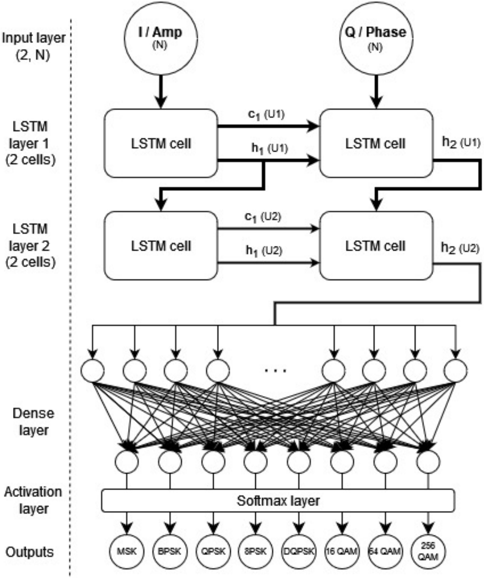


Conventional two-layer LSTM model. The input signal has temporal length N, and the hidden unit dimensions of the two LSTM layers are U_1 and U_2.



Alternative two-layer LSTM model. The input signal has temporal length N, and the hidden unit dimensions of the two LSTM layers are U_1 and U_2.

Alternative LSTM Model: Physical Interpretation

Physical Meaning

- Models **constellation dynamics** directly
- Captures **covariance** between I/Q amplitudes across the entire signal

Advantages and Trade-offs

Advantages:

- **10x faster training** (18–19s vs. 380–401s per epoch)
- More stable performance at **low SNRs**
- Mitigates early overfitting

Trade-offs:

- Reduced temporal depth → fewer long-range dependencies
- Lower accuracy at high SNRs (compensated by adding layers)

Model Performance: 128-Sample Inputs

Key Metrics

	CNN	**Conv LSTM (IQ)**	**Alt LSTM (IQ)**
Number of Epochs	7	33	20
Epoch Avg. Duration [s]	182	380	**18**
Training Accuracy [%]	58.88	66.05	50.25
Validation Accuracy [%]	52.50	**60.31**	46.68

Takeaways

- **Conv LSTM** achieves the highest validation accuracy (**60.31%**).
- **Alt LSTM** is **20x faster per epoch** than Conv LSTM.
- **CNN** offers a balanced approach.

Trade-off: Accuracy vs. Training Speed

Results-Confusion Matrices: IQ Inputs (128 Samples)

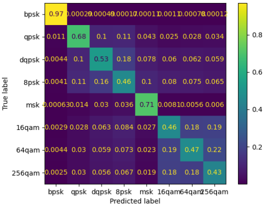


Figure: CNN Model

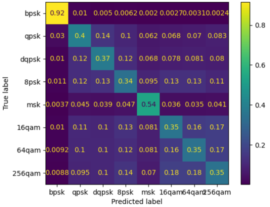


Figure: Alt LSTM Model

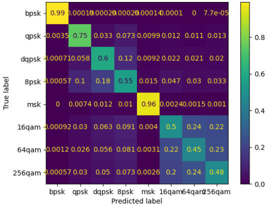


Figure: Conv LSTM Model

Observations

- Conv LSTM shows the clearest class separation.
- Alt LSTM struggles with QAM modulations.
- CNN misclassifies high-order QAMs as lower-order.

Confusion matrices for models trained on IQ inputs (validation set)

Conclusion: Balancing Performance and Efficiency

Key Findings

- **Trade-offs**: Accuracy, computational time, and waveform length must be balanced for optimal performance.
- **Performance Gains**:
  - Training time reduced by $>$**90%**
  - Accuracy improved by **up to 13.4%** at low SNRs
- **Innovation**: LSTM transformed into a **deep feature extractor**, capturing nuanced relationships between I/Q components.
- **Limitations**: Longer input sequences required for high-SNR accuracy compared to conventional models.
- **Future Work**: Need for **real-world or more realistic data** to validate and refine the approach.

Q&A and Discussion

Thank you for your attention !

Any questions or remarks ?