Poster 23

# Machine Learning for Automatic Mobile-Wireless Modulation Classification

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## 1. Background

- Automatic Modulation Classification (AMC) enables the autonomous identification of signal modulation schemes, advancing both military defense systems and civilian telecommunications through **improved security** and **operational efficiency**.
- Machine Learning (ML) can enhance AMC by **adaptively recognizing** and **classifying** complex signal patterns, potentially boosting future receivers' accuracy in signal interpretation.

## 2. Objectives

- Develop a simulation framework in MATLAB & Simulink for **dataset generation** from **modulated signals**.
- Design and train a **ML model** for AMC, integrating a novel **augmented loss function**.
- **Quantize** pre-trained ML models for computational efficiency and potential hardware deployment.

## 3. Data Generation

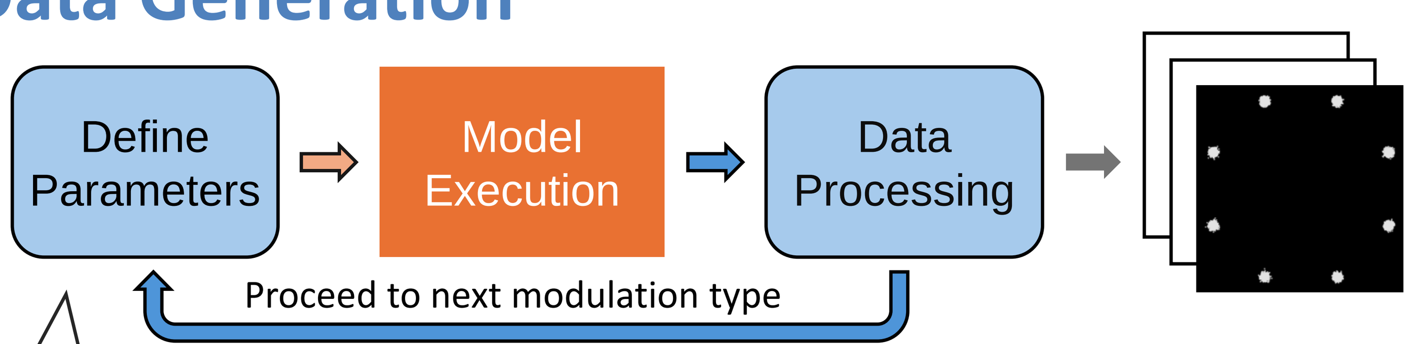



*Figure 1: Data generation process by MATLAB and Simulink*

**Changeable Parameters (MATLAB)**

- Signal characteristics ($A, f, \varphi$)
- Modulation type
- Samples per signal
- Simulation time
- Carrier frequency
- Amount of images
- SNR value
- Other channel effects...

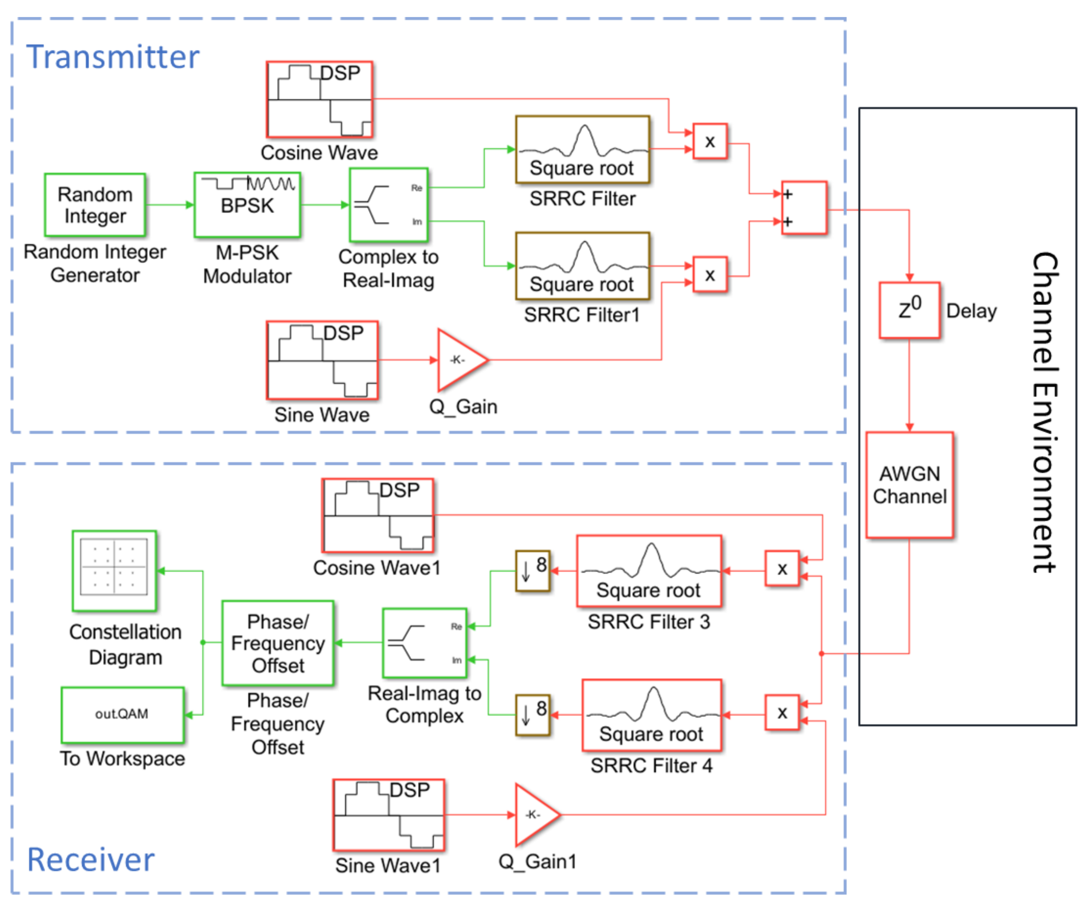
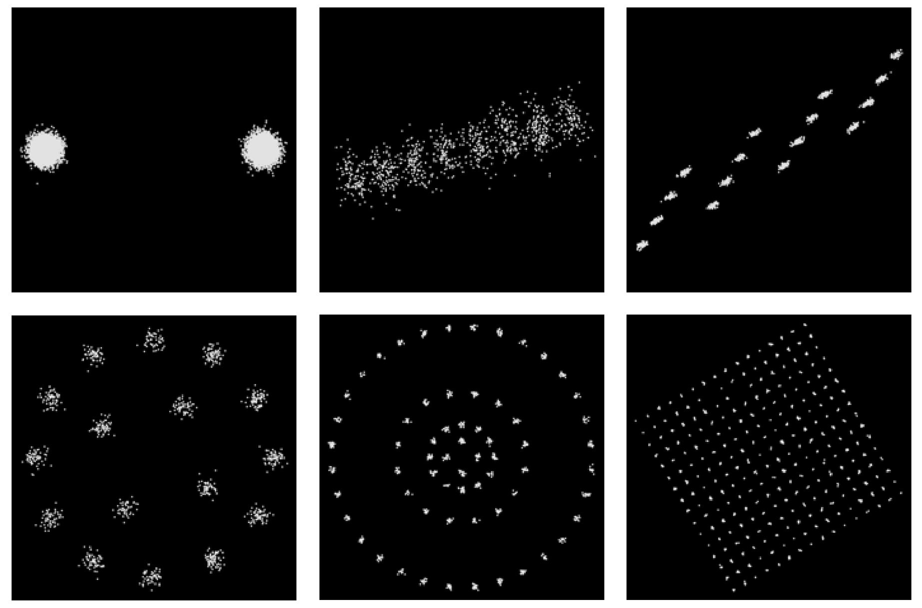



*Figure 2: Simulink Model for Communication Channel Simulation*

## 4. Datasets

- Constellation images:
  - **Single-channel**
  - **224x224 pixels**
  - **Normalized pixel value**
  - **Batch size of 64 employed**



*Example constellation images in dataset*

| Dataset | Modulation and channel effect | Total images |
|---|---|---|
| 1 | B/Q/8-PSK, 16/64/256-QAM<br>AWGN, Quadrature error, I/Q imbalance | 10800 |
| 2 | B/Q/8-PSK, 16/64/256-QAM, 4/8-PAM<br>AWGN, Quadrature error, I/Q imbalance, Phase offset, Clock offset | 28800 |
| 3 | B/Q/8-PSK, 16/64/256-QAM, 4/8-PAM, 16/32/64-APSK<br>AWGN, Quadrature error, I/Q imbalance, Phase offset, Clock offset | 39600 |

***Table 1:** Dataset Composition*

## 5. Machine learning and Model Quantization

- The ML methodology employed in this study mainly focused on the **Convolutional Neural Networks (CNN).**

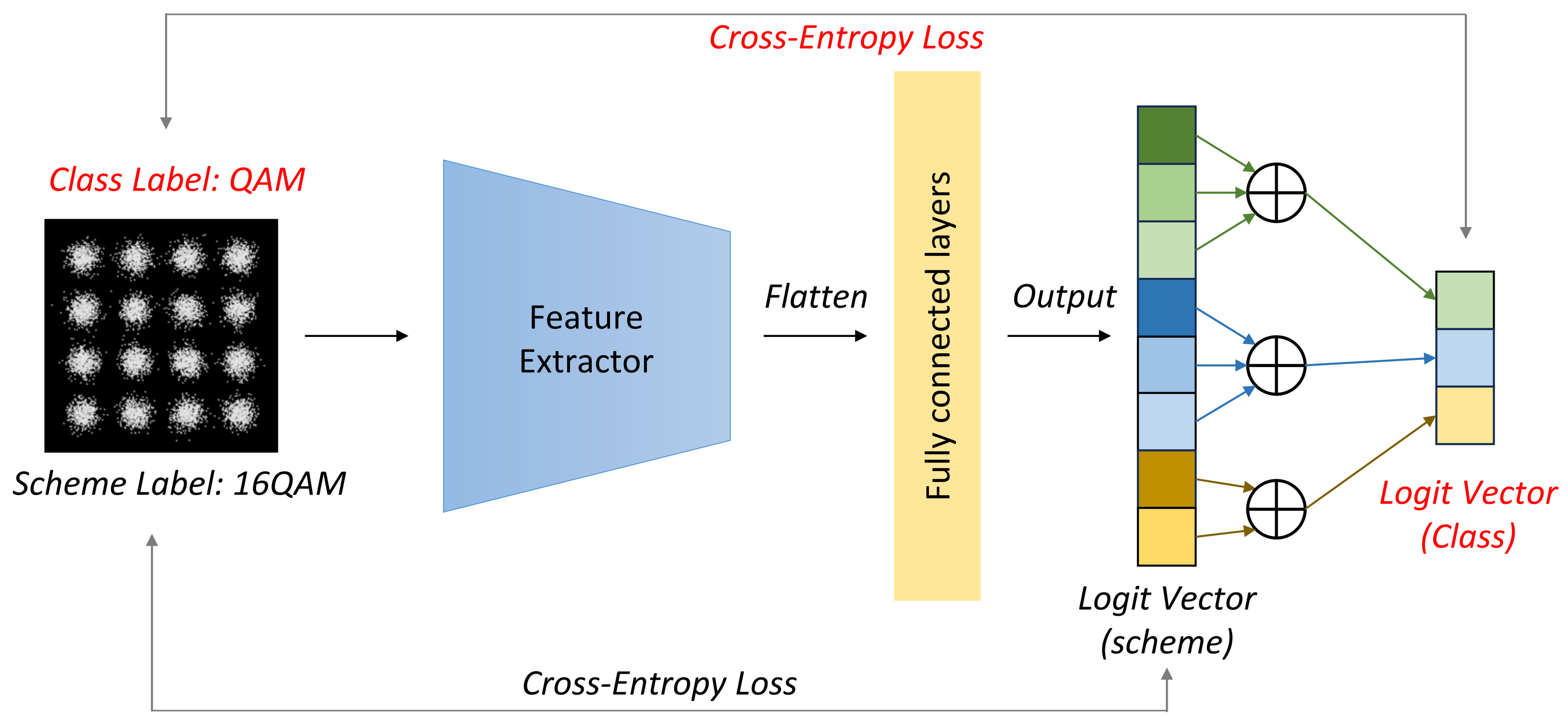



*Figure 3: Pipeline of ML model with additional loss function*

- **CNN-based** feature extractor
- Modulation scheme's **class label** added for additional training loss:

$$l_{total} = w_{scheme} l_{scheme} + w_{class} l_{class}$$

- **No increase** in the model's computational overhead

- *Quantization on PyTorch* [1] used for quantizing models
- Model Parameter: **32-bit floating point** to **8-bit integer** data type
- Quantized Model size reduced to **one-fourth** of the original model

## 6. Result analysis

- Models were trained for 50 epochs.
- Figure 4 illustrates the stable and efficient convergence of our model.

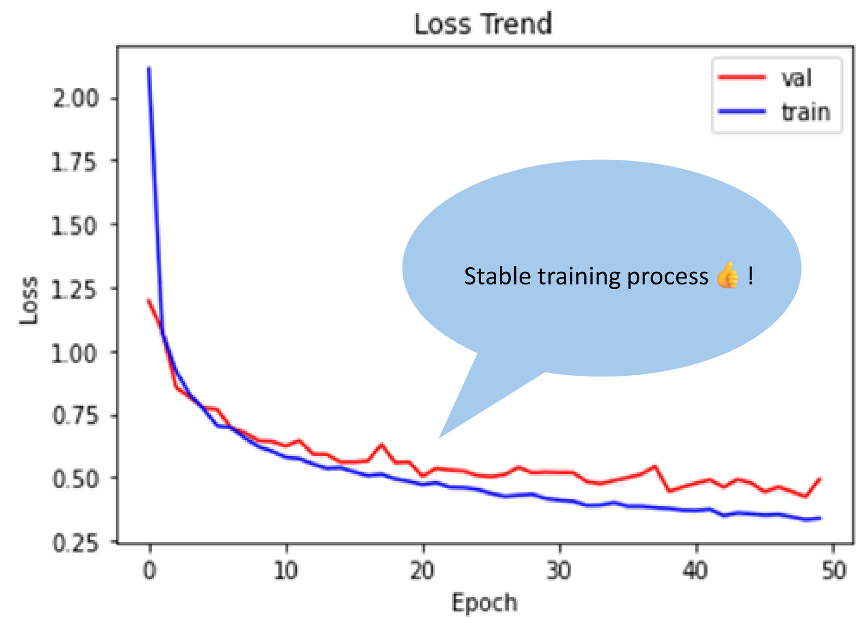



***Figure 4:** Loss trajectory during training*

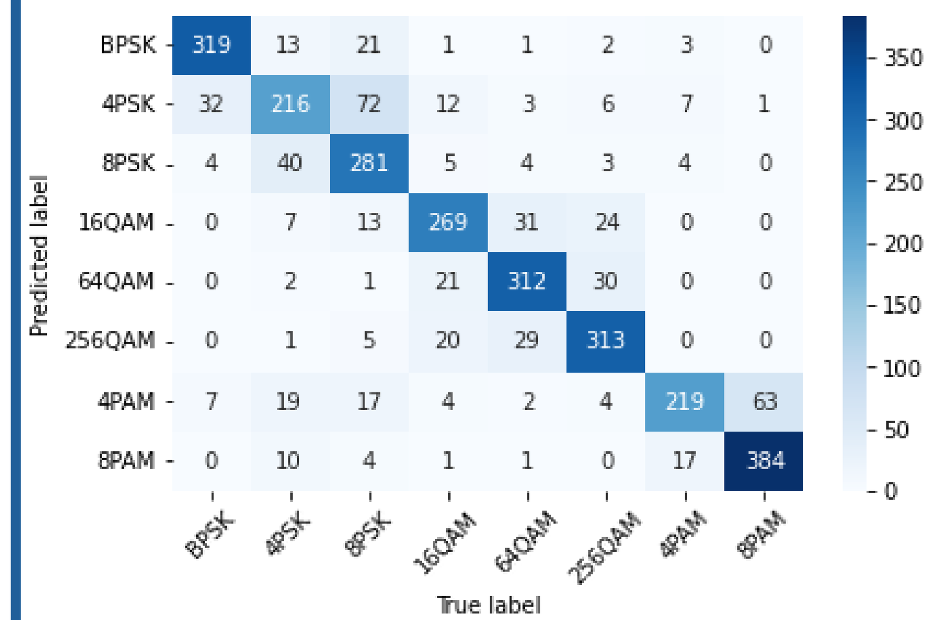



***Figure 5:** Confusion matrix of Dataset 2*

| Dataset / Accuracy | 1 | 2 | 3 |
|---|---|---|---|
| Scheme (%) | 100 | 83.9 | 81.2 |
| Class (%) | 100 | 95.6 | 91.1 |
| Quantized Scheme (%) | 100 | 80.4 | 78.9 |
| Quantized Class (%) | 100 | 93.0 | 90.2 |

***Table 2:** Dataset's optimal results*

## 7. Conclusions and Future work

- A Simulink model excels in simulating communication channels and creating dataset for ML.
- High performance ML models (**above 80% accuracy**) for constellation image-based AMC.
- Introduced a knowledge-based loss function, enhancing ML training process with **strong explainability**.
- An efficient quantization method prepares the model for hardware use with **minimal accuracy loss** (< 3%).
- Future work will consider including more real-world channel effects into dataset and implementing the quantized ML model on a *RFSoC 4×2* platform [2] as a hardware accelerator.

## Reference

[1] https://pytorch.org/blog/introduction-to-quantization-on-pytorch/
[2]https://www.amd.com/en/corporate/university-program/aup boards/rfsoc4x2.html