Distributed Deep Learning for Modulation Classification in 6G Cell-Free Wireless Networks IMPLEMENTATION

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Primarily focused on **Automatic Modulation Classification(AMC):**

The three approaches implemented are:

- Centralized Model
- Distributed Model
- Hybrid Model

All models were trained on a synthetically generated dataset representing IQ signals received by multiple radio units under various modulation schemes and signal-to-noise ratios (SNRs)

Dataset Generation

To simulate real-world communication conditions:

- Random binary data was modulated using BPSK, QPSK, 16QAM, and 64QAM schemes.
- Signals passed through a flat Rayleigh fading channel with additive white Gaussian noise (AWGN).
- Each signal was received by **3 RUs**, producing different channel conditions.
- For each combination of modulation type and SNR (from -10 dB to 30 dB in 2 dB steps), **1024 frames** were generated with **1024 samples per frame**.
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The generated data was split into training, validation, and test sets (75%-12.5%-12.5%) and saved as "modulation_dataset.npz"

Model Architectures

3.1 Centralized Model

- **Assumption:** All IQ samples from all RUs are available centrally and can be coherently combined using Equal Gain Combining (EGC).
- **Architecture:** ResNet-style 1D CNN with residual blocks and global average pooling.
- **Input:** Combined IQ data from 3 RUs.
- **Output:** Modulation class (one-hot encoded).

3.2 Distributed Model

- **Assumption:** Each RU processes its own IQ samples and sends only soft decisions (probabilities) to the DU.
- **Components:**
  - RU Model: Identical ResNet-like CNN for each RU.
  - Voting Model: Concatenates soft decisions from all RUs and outputs the final prediction.

3.3 Hybrid Model

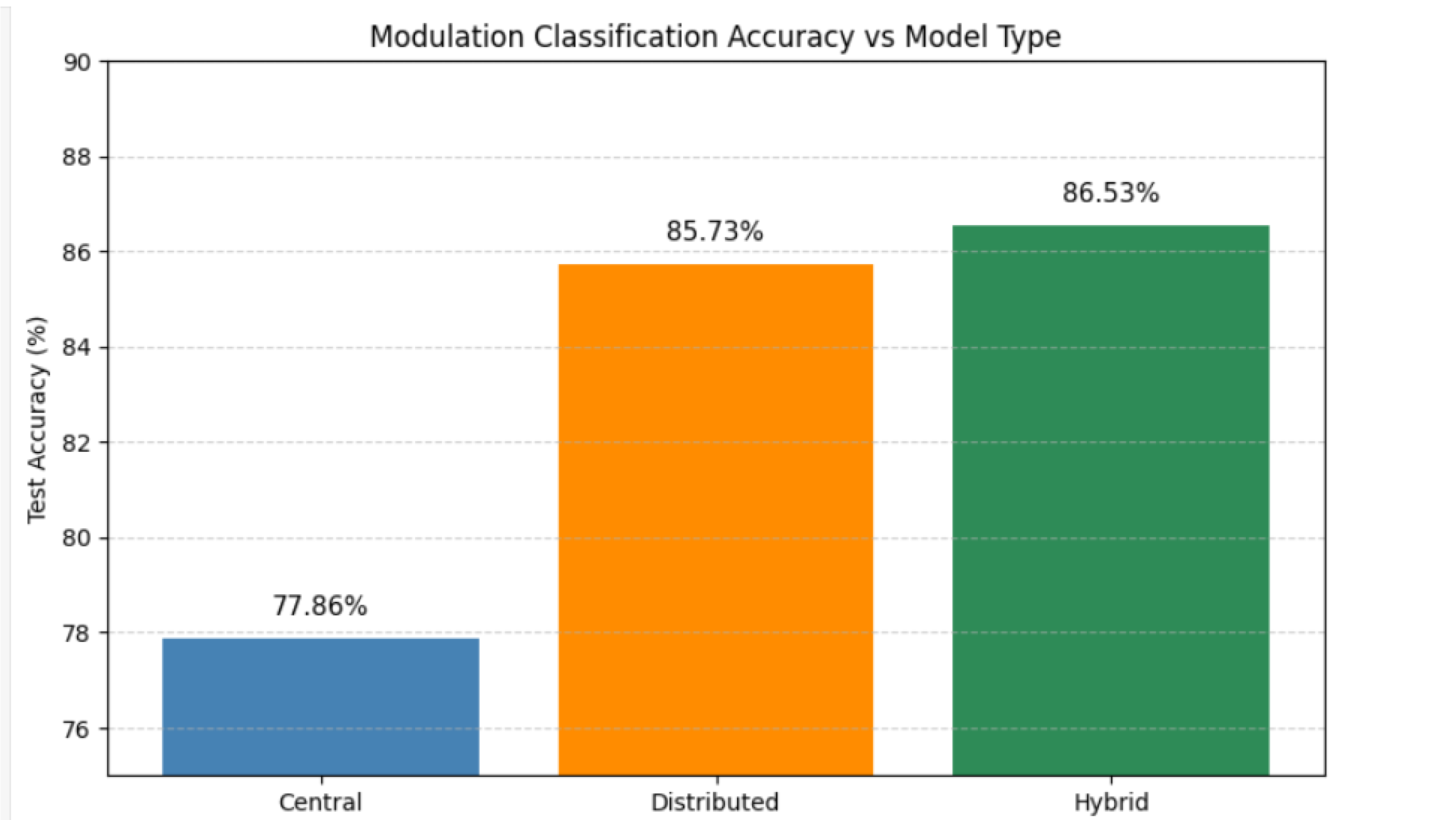
- **Assumption:** Each RU sends both its soft decision and IQ samples to the DU.
- **Components:**
  - RU Models (frozen after training).
  - DU Model processes the combined IQ data (via EGC).
  - Voting Model combines outputs from both RU soft decisions and DU features.

Training Details

- Optimizer: Adam
- Loss Function: Categorical Crossentropy
- Batch Size: 64
- Epochs: 10 (with early stopping on validation accuracy)

All models were trained using TensorFlow/Keras.

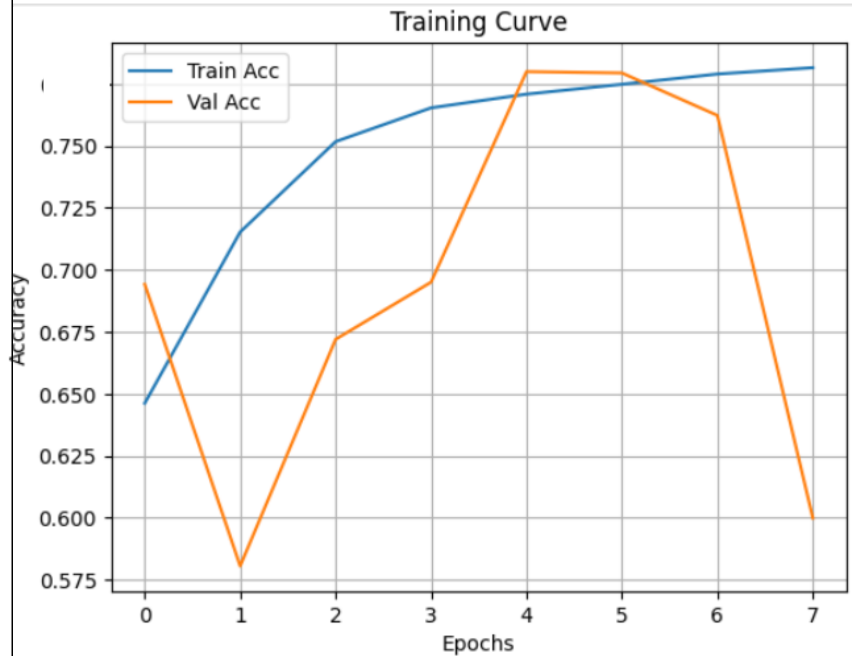
Results



The hybrid model achieved the **best accuracy**, leveraging both distributed soft decisions and centralized EGC IQ features.

CENTRAL MODEL:

```
336/336 ━━━━━━━━━━━━━━━━━━━━ 7s 20ms/step - accuracy: 0.7804 - loss: 0.4769
    Test Accuracy: 77.86%
```




```
Epoch 10/10
1008/1008 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8648 - loss: 0.2962 - val_accuracy
    Test Accuracy (Distributed Model): 85.73%


    Hybrid Model Test Accuracy: 86.53%
```