

Federated On-Device Training on Arduino Nano 33 BLE

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Project Context

- Course: **Machine Learning for IoT**.
- Hardware: **Arduino Nano 33 BLE** + TinyML Shield.
- Sensors: **IMU** – accelerometer, gyroscope, orientation.
- Target task: classify IMU segments into multiple classes (e.g., gestures / movements in “Spell Game”).
- Constraint: training **directly on the board** with very limited RAM and compute.

Why Federated Learning on Tiny Devices?

- In many IoT scenarios, there are **multiple devices** observing related data distributions.
- Sending raw sensor data to a server is:
 - Bandwidth expensive.
 - Potentially privacy sensitive.
- Federated learning idea:
 - Each device trains a **local model** on its own data.
 - Devices only exchange **model parameters**, not raw data.
- Question: **Can we implement a simple federated scheme directly between two Nano 33 BLE boards?**

Raw Data from Edge Impulse

- Data collected with Edge Impulse pipeline.
- Stored as .cbor messages:
 - Payload includes: `interval_ms`, `sensors`, `values`.
 - Each sample: around **2000 ms**, sampled at **100 Hz**.
- Shape of values:

$$(T, 9) \approx (201, 9),$$

where 9 channels are (accel, gyro, orientation).

% Placeholder for raw CBOR / time-series visualization

Why Not Use Raw 201×9 Data on Board?

- Flattened vector length: $201 \times 9 = 1809$ features.
- With 32-bit floats, a single sample already takes:

$$1809 \times 4 \approx 7.1 \text{ kB.}$$

- On-device training uses:
 - Training data buffer.
 - Network weights and gradients.
 - Stacks, BLE buffers, etc.
- Conclusion: **too large** for robust on-board training.
- Solution: **compress each segment into 75 scalar features.**

75-D Feature Extraction (Python)

- For each segment $v \in \mathbb{R}^{T \times 9}$:
 - Global statistics per channel (9 dims):
 - mean, std, min, max $\Rightarrow 9 \times 4 = 36$.
 - Split time into 3 segments:
 - mean in each segment $\Rightarrow 3 \times 9 = 27$.
 - Per-channel energy:

$$\text{energy} = \frac{1}{T} \sum_t v_{t,c}^2 \Rightarrow 9 \text{ dims.}$$

- Magnitude RMS for 3 groups (accel / gyro / orientation):

$$\text{RMS}_{\text{acc}}, \text{RMS}_{\text{gyro}}, \text{RMS}_{\text{ori}} \Rightarrow 3 \text{ dims.}$$

- Total: $36 + 27 + 9 + 3 = \mathbf{75}$ features per sample.

Train / Val / Test Split

- Python preprocessing:
 - Read all training and testing .cbor files.
 - Convert to $X \in \mathbb{R}^{N \times 75}$, label vector y .
 - Map label names (e.g., circle, noise) to integers.
 - Randomly shuffle and split into:
 - Train.
 - Validation.
 - Test.
- Store as .npz for PC training and also export as data.h for Arduino.

% Placeholder for class distribution / split visualization

Network Architecture on Nano 33 BLE

- Simple fully connected network:

$75 \rightarrow 64 \rightarrow \text{classes_cnt.}$

- Activation:
 - Hidden layer: ReLU.
 - Output layer: softmax.
- Loss:
 - Cross-entropy between predicted probabilities and one-hot labels.
- Implemented in C with:
 - Manually allocated layers and neurons.
 - Forward and backward propagation using SGD.

On-Device Data & Normalization

- `data.h` contains:
 - `train_data[train_cnt][75]`.
 - `validation_data[val_cnt][75]`.
 - `test_data[test_cnt][75]`.
 - `train_labels`, `validation_labels`, `test_labels`.
 - Feature-wise `feature_min[75]`, `feature_max[75]` from train set.
- Before feeding to the network (on board):

$$x'_j = \frac{x_j - \text{feature_min}_j}{\text{feature_max}_j - \text{feature_min}_j}.$$

- Normalization is implemented as a small C function operating on the `input[]` buffer.

Baseline: Local On-Device Training

- Optimizer: **SGD** with fixed learning rate.
- Example parameters:
 - `#define LEARNING_RATE 0.0015`
 - `#define EPOCH 50`
- Training loop on board:
 - Shuffle training indices.
 - For each sample:
 - 1 Load feature vector into `input []`.
 - 2 Normalize using `feature_min/max`.
 - 3 Forward propagation.
 - 4 Backward propagation, update weights.
- Accuracy monitored on train / val / test after each epoch.

From Single Board to Federated Setup

- We have (at least) **two** Nano 33 BLE boards:
 - Each board has its own local dataset (e.g., different users / recording sessions).
- Idea:
 - Each board trains locally for several epochs.
 - Boards use BLE to **exchange network weights**.
 - Then **average** the weights as a simple federated aggregation.
- No raw sensor data is transmitted.

Parameter Packing for BLE

- In the C code, the network is represented as:
 - Layers $L[i]$.
 - Neurons with weight vector $W[]$ and bias B .
- Function `packUnpackVector(Type)`:
 - PACK: serialize all weights and biases into a flat `WeightBiasPtr[]` buffer.
 - UNPACK: read back from buffer to local network.
 - AVERAGE: average between received buffer and local network and update both.
- This buffer is then sent via BLE characteristic(s) between the two boards.

Simple Federated Averaging

- In standard FedAvg:

$$w^{(t+1)} = \sum_k \frac{n_k}{N} w_k^{(t+1)},$$

where w_k is client k 's local weights.

- In our prototype with two boards:
 - Use equal weighting as an approximation:

$$w_{\text{new}} = \frac{w_A + w_B}{2}.$$

- Implemented in `packUnpackVector(AVERAGE)`.
- Federated round:
 - 1 Each board trains locally for some epochs.
 - 2 Exchange weight buffers via BLE.
 - 3 Average and update local networks.

Federated Training Schedule

- Example schedule:
 - Local epochs per round: E (e.g., 1–5).
 - Number of federated rounds: R .
- On each board:
 - 1 Repeat local training for E epochs.
 - 2 Pack parameters and send to peer via BLE.
 - 3 Receive peer parameters into buffer.
 - 4 Call `packUnpackVector(AVERAGE)` to update network.
- Trade-off:
 - Larger E : fewer communications, more local drift.
 - Smaller E : more communication, better synchronization.

PC-Side Reference Training (PyTorch)

- Use the same 75-D features and labels in Python:
 - Network: 75-64-classes_cnt.
 - Loss: cross-entropy.
 - Optimizer: **Adam**.
- Observations:
 - Adam with hundreds of epochs can train the network to a good accuracy.
 - Simple SGD (without momentum, on the PC) is much harder to tune and converges slowly.
- PC model acts as an **upper bound** for the on-device performance.

% Placeholder for PC training curves (Adam vs SGD)

Comparing Local vs Federated On-Device Training

- Baseline: Each board trains independently on its own data.
 - May overfit to its own user / recording style.
- Federated version:
 - Periodic parameter exchange and averaging.
 - Helps share knowledge about different local distributions.
- Metrics to compare:
 - Training accuracy on each board.
 - Validation / test accuracy using a held-out set (from PC).

% Placeholder for accuracy curves: local vs federated

Limitations

- **Optimizer:** on-device training uses plain SGD; no Adam or momentum due to:
 - Code complexity.
 - Extra memory for moment estimates.
- **Communication:**
 - BLE bandwidth is limited.
 - Transmitting full parameter vector can be slow.
- **Scalability:**
 - Prototype only tested with two boards.
 - No central server; logic is peer-to-peer.

Possible Improvements

- On-device optimization:
 - Implement lightweight variants of Adam / momentum, or adaptive learning rate schedules.
- Model compression:
 - Quantize weights / send only deltas to reduce BLE traffic.
- Protocol:
 - Generalize from 2 boards to K devices, with either a central aggregator or a gossip protocol.
- Data:
 - Collect more user-specific IMU trajectories to better demonstrate personalization + federated averaging.

Summary

- Built a **full pipeline**:
 - Raw IMU segments \Rightarrow 75-D features.
 - Python preprocessing and PC training.
 - Exported data.h for on-device training.
- Implemented a small **on-device neural network**:
 - 75-64-classes_cnt, ReLU + softmax, SGD training.
- Designed and tested a **federated learning prototype**:
 - Two Nano 33 BLE boards exchanging weights via BLE.
 - Simple parameter averaging after local training epochs.
- Demonstrated that even with tight resource constraints, federated ideas can be prototyped on microcontrollers.

Thank you for listening!