

Federated Spellcasting Battle System

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December 2025

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Task

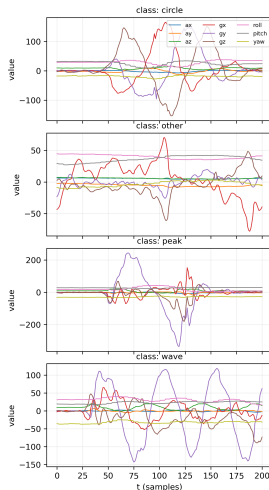
- Hardware: **Arduino Nano 33 BLE** + TinyML Shield.
- Sensors: **IMU** – accelerometer, gyroscope, orientation.
- Target task: classify IMU segments into multiple gestures / movements in “Spell Game”.
- Federated learning on two boards, communication through BLE
- Constraint: training **directly on the board** with very limited RAM and compute. BLE transmitting limitation.

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).



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.

Network Architecture on Nano 33 BLE

- Simple fully connected network:

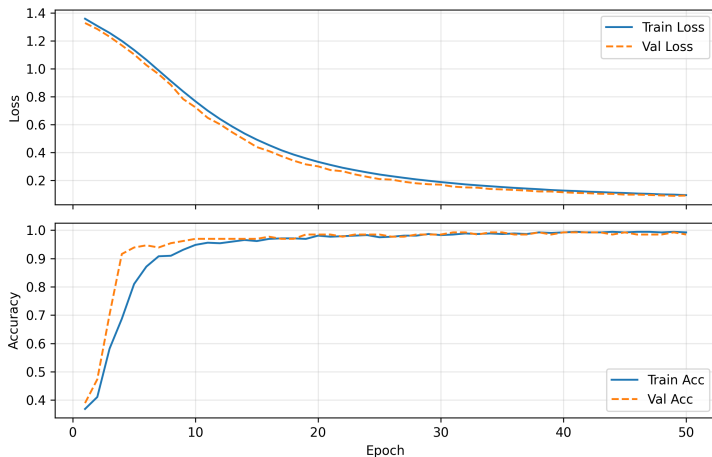
$75 \rightarrow 64 \rightarrow \text{classes_cnt.}$

- 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.

PC-Side Reference Training (PyTorch)

- Use exactly the same 75-D feature vectors as on the Arduino:
- Results:
 - After about 50 epochs, validation accuracy reaches $\approx 95\%$.
 - This PC model is used as an **upper-bound reference** for on-device learning performance.

Training / Validation Curves



PC-side centralized training reaches $\sim 95\%$ val. accuracy in ~ 50 epochs.

From Single Board to Federated Setup

- Two boards have their own local dataset from different users' gesture recordings.
- Network: $75 \rightarrow 32 \rightarrow \text{classes_cnt}$ due to the BLE Maximum Transmission Unit
- Idea: In each round
 - Each board trains locally for every epoch.
 - Boards use BLE to **exchange network weights**.
 - Then **average** the weights as a simple federated aggregation.
- **Only parameters are sent over BLE.** No raw sensor data is transmitted.
- Our federated on-device training protocol is based on an open-source GitHub repository.

Reference:

<https://github.com/niil87/Machine-Learning-for-IOT--Fall-2022-Batch-Lun>

BLE Communication

Board A: Leader (BLE Peripheral)

- Advertises BLE service MLeader and accepts a connection.
- **Sends** the current **global weights** over BLE (split into batches).
- **Receives** updated weights from Board B over BLE.
- Aggregates parameters and starts the next round.

Board B: Worker (BLE Central)

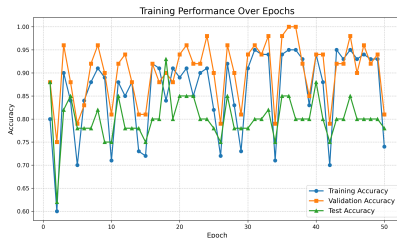
- Scans for MLeader, connects, and subscribes to updates.
- **Receives** global weights over BLE and loads them into the NN.
- Runs **local on-device training** on its own IMU dataset.
- **Uploads** its updated weights back to Board A over BLE.

Simple Federated Averaging

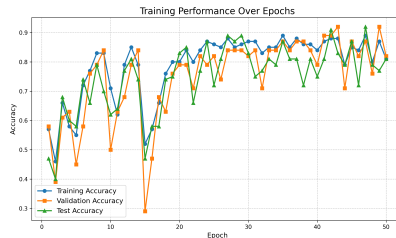
- In our prototype with two boards: Use equal weighting as an approximation:

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

On-Device Training Curves



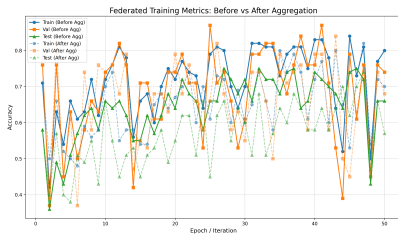
Local Train with data_byh



Local Train with data_fje

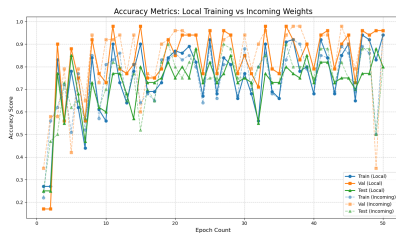
- Federated training improves **cross-user generalization** without sharing raw IMU data.

On-Device Training Curves



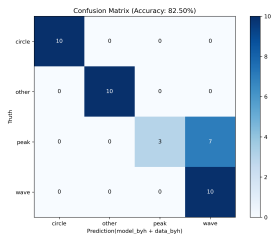
Performance Comparison: Local vs.
Federated Training on Leader

- Federated training improves **cross-user generalization** without sharing raw IMU data.



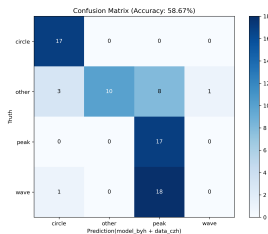
Performance Comparison: Local vs.
Federated Training on Worker

Confusion Matrices: Local Training one Board



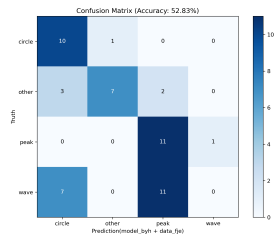
Train byh → Test byh

acc = 82.50%



Train byh → Test czh

acc = 58.67%

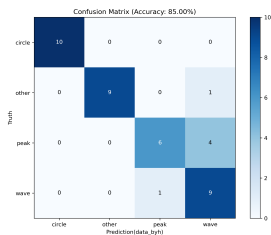


Train byh → Test fje

acc = 52.83%

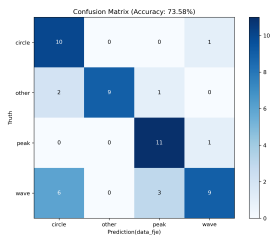
- Best performance on **in-domain** test (A→A).
- Accuracy drops on B/C due to **non-IID** user motion patterns.

Confusion Matrices: Federated Training (fje+byh, FedAvg)



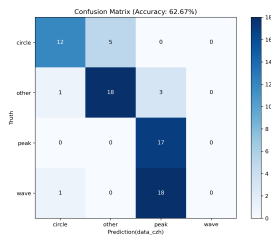
FedAvg → Test byh

acc = 85.00%



FedAvg → Test fje

acc = 73.58%



FedAvg → Test czh

acc = 62.67%

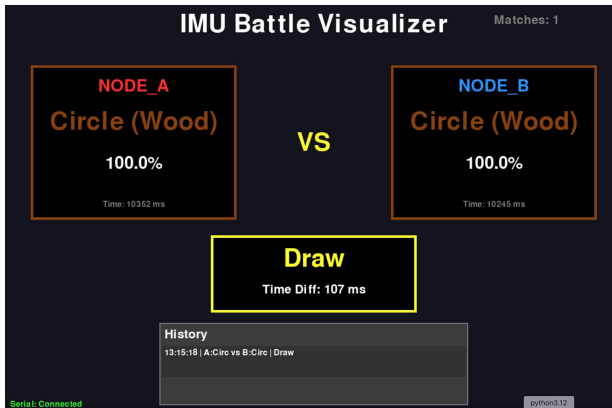
- Federated model reduces cross-user confusion compared to local models.
- Gains come with communication cost (BLE weight exchange each round).

SpellGame Battle

- Two Nano 33 BLE boards (NODE_A & NODE_B) perform **real-time gesture inference** on 2-second IMU windows.
- PC visualizes gestures and determines winner using rock-paper-scissors rules:

circle > wave > peak > circle

- Predicted gestures are transmitted to the **IMU Battle Visualizer** (PC-based GUI).
- PC displays:
 - Both players' detected gestures simultaneously.
 - **History log** of past matches.
 - **Battle outcome** to verify inference accuracy and cross-user generalization.



Stability Issues Observed:

- Interface occasionally fails to **synchronize or display both gestures simultaneously**.
- **Hypothesized causes:**
 - BLE packet delays disrupt real-time data flow.
 - Temporal misalignment: users trigger gestures at different moments.

Demo Video

Click to watch demo

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.
- Build a Federated Spellcasting Battle System

Thank you for listening!