Indoor Positioning Systems
Edge-based RF Fingerprinting

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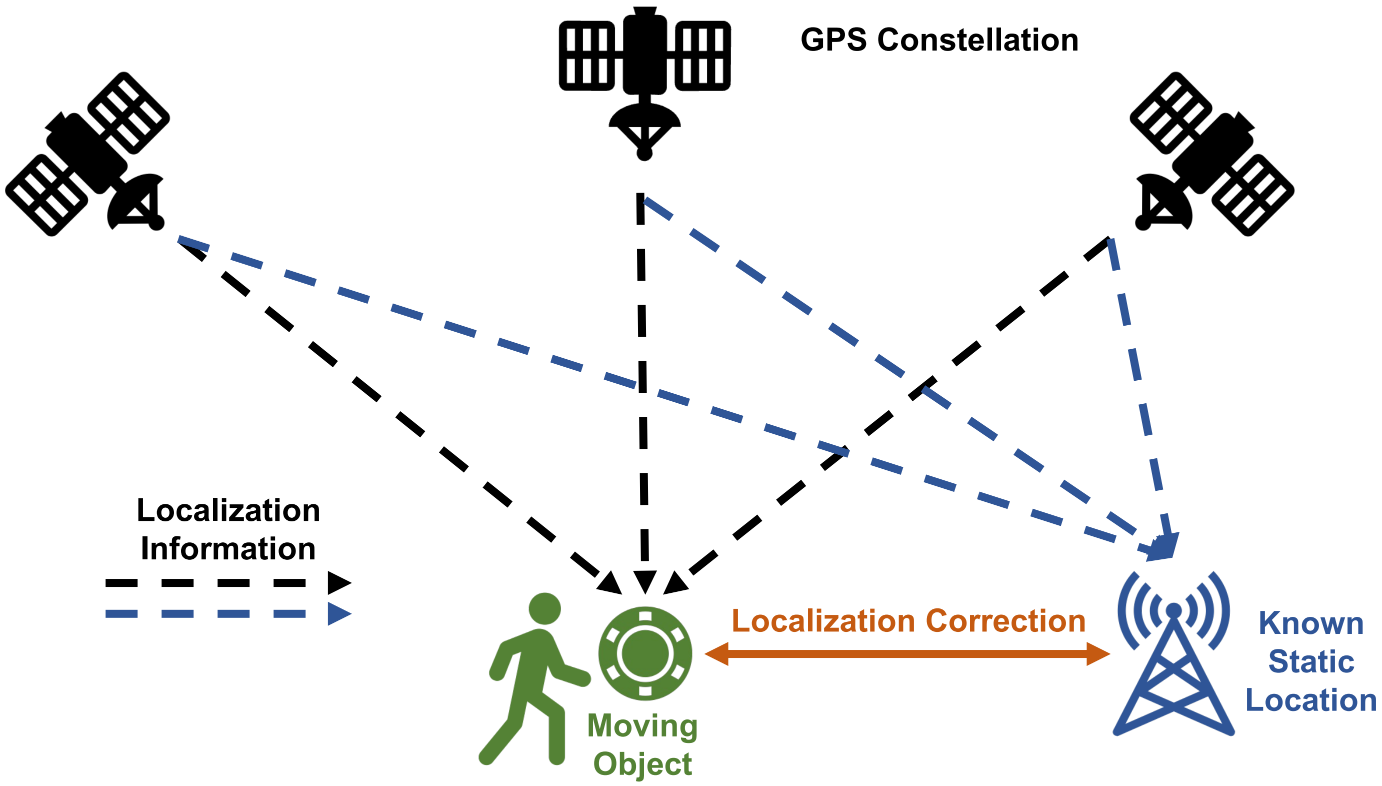
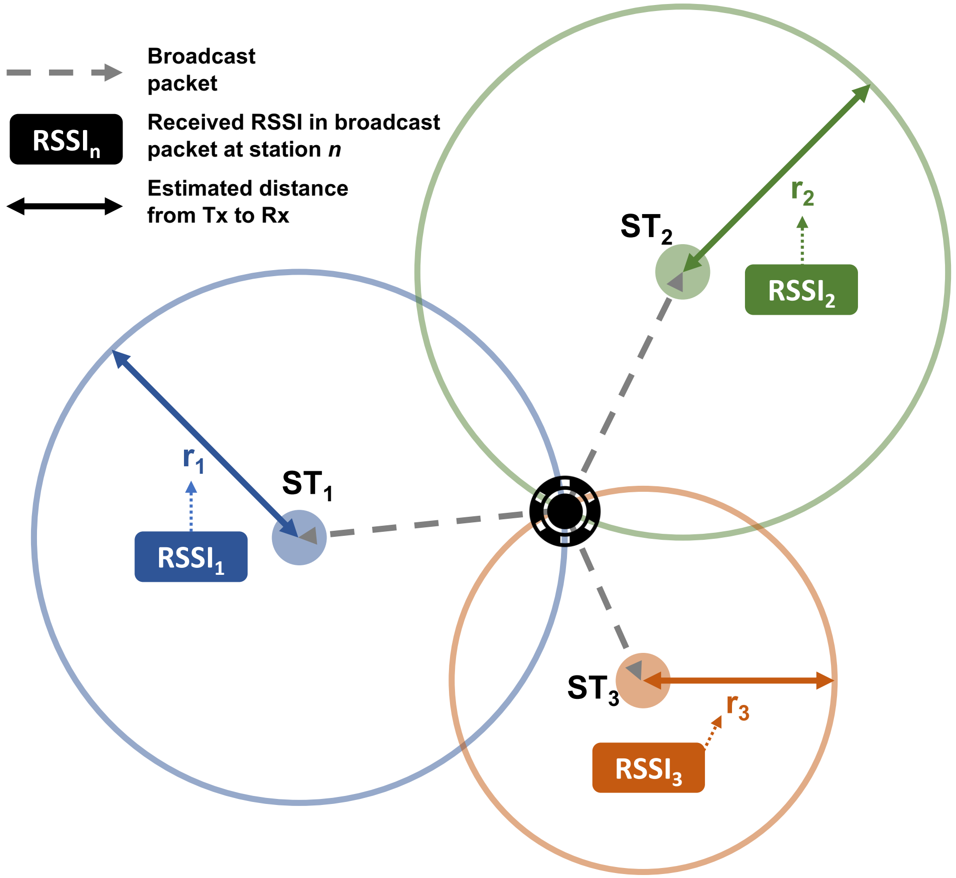
ICTP

TINY ML edu

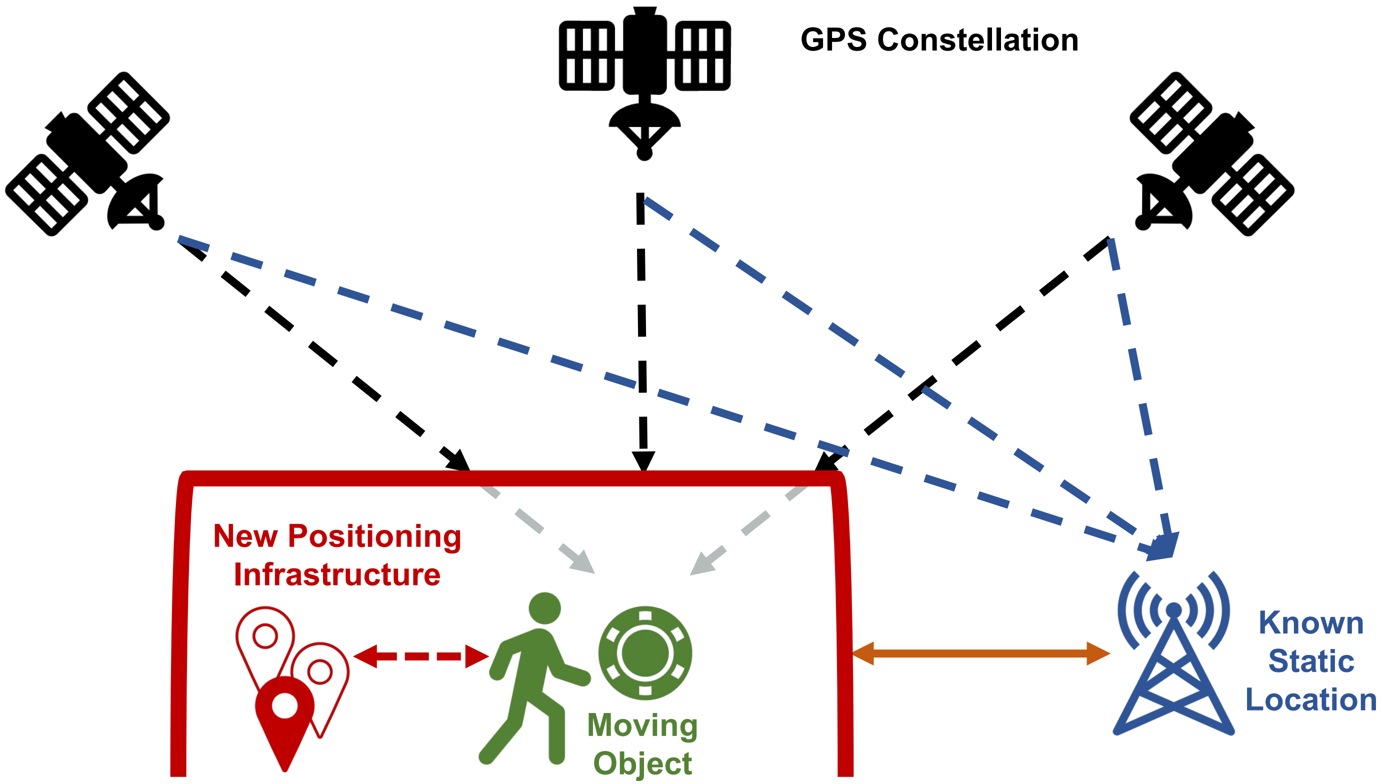
May 10th, 2024

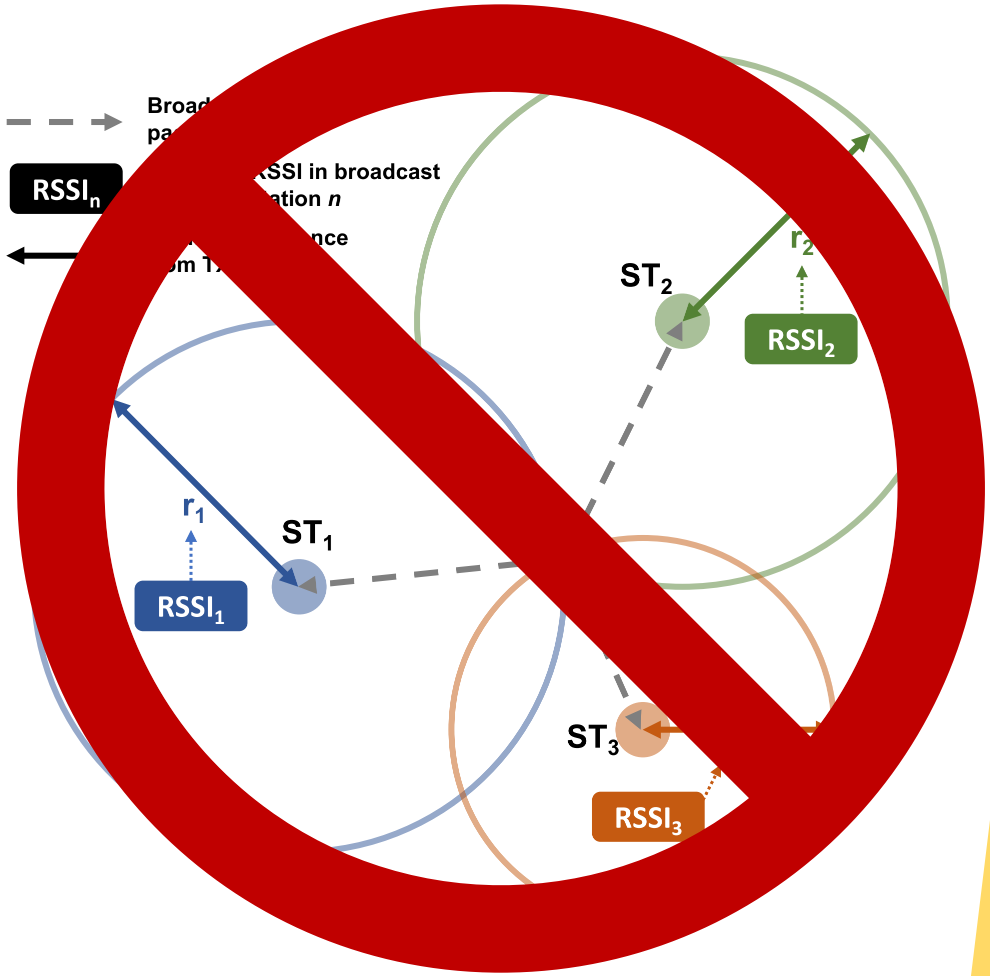
Outdoor Positioning and Tracking (trilateration)



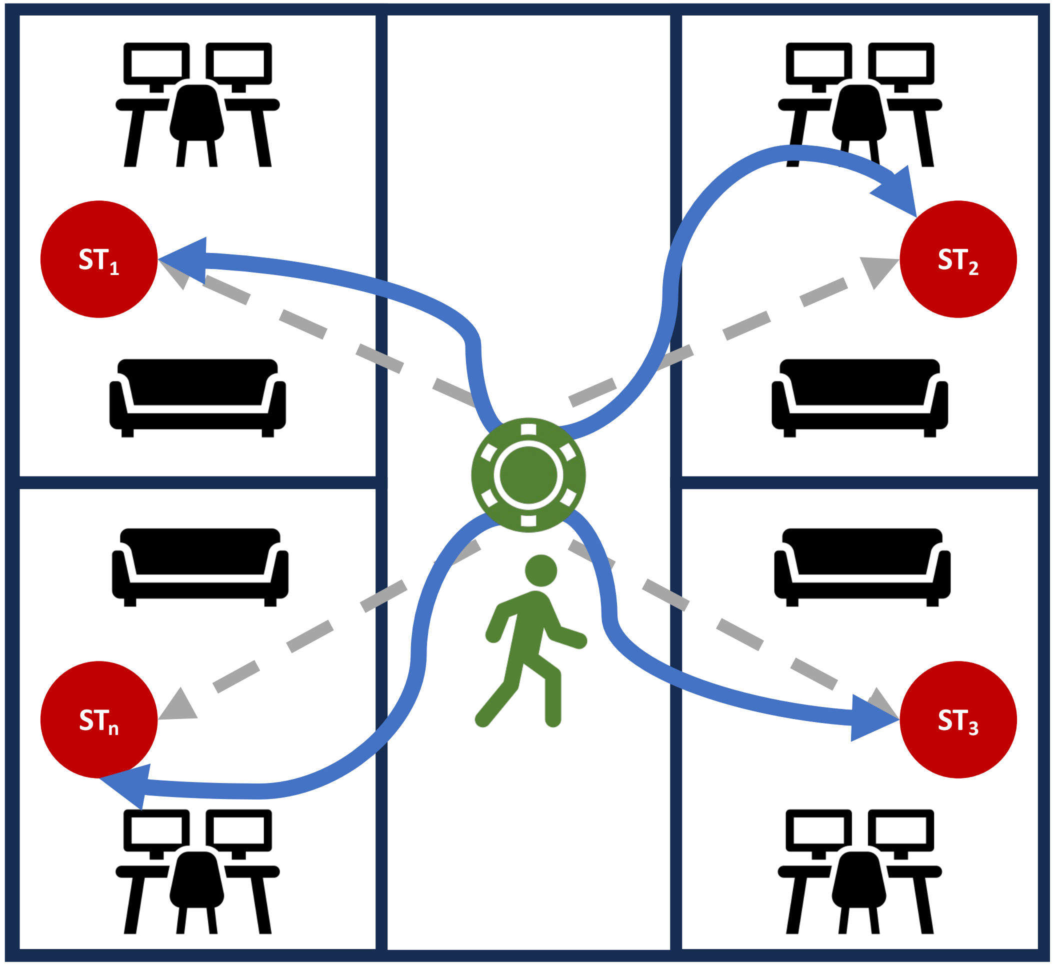


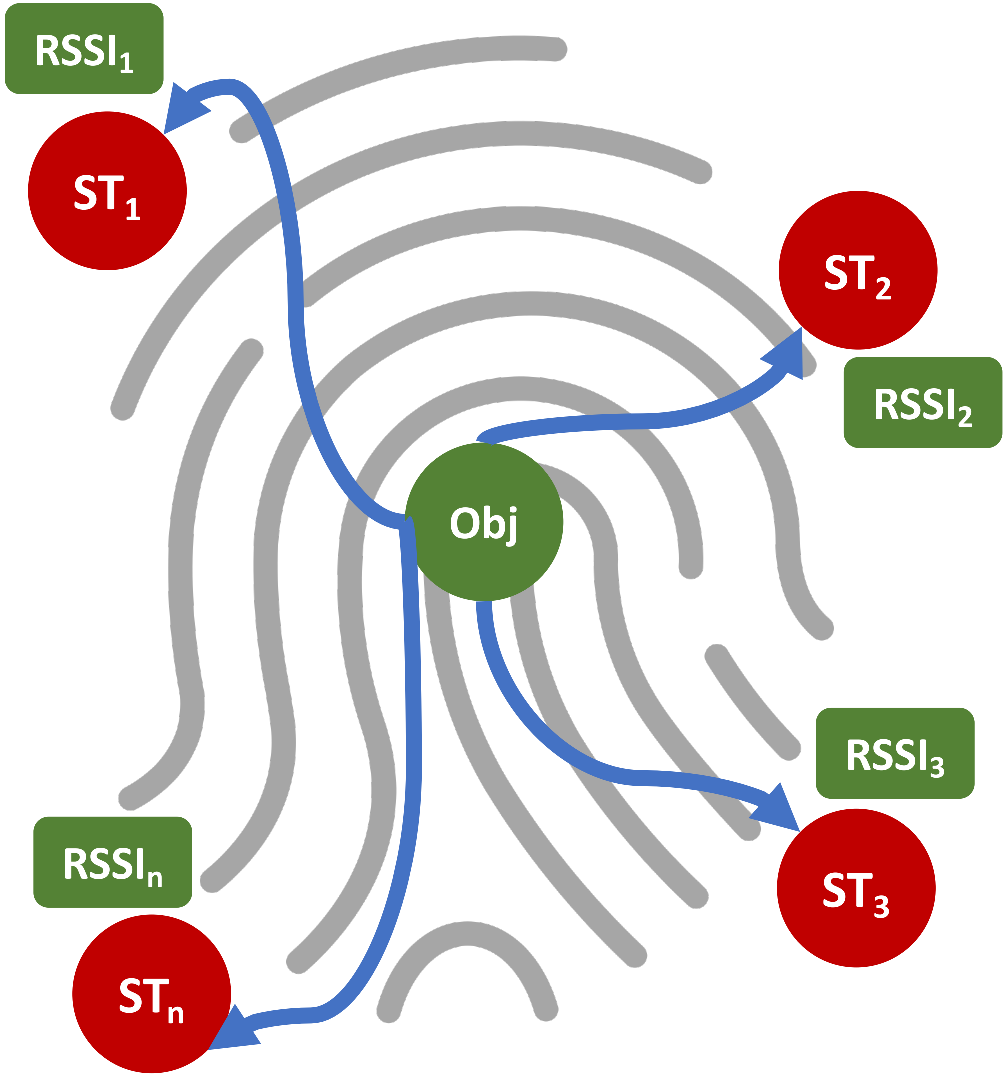
Indoor Scenario?



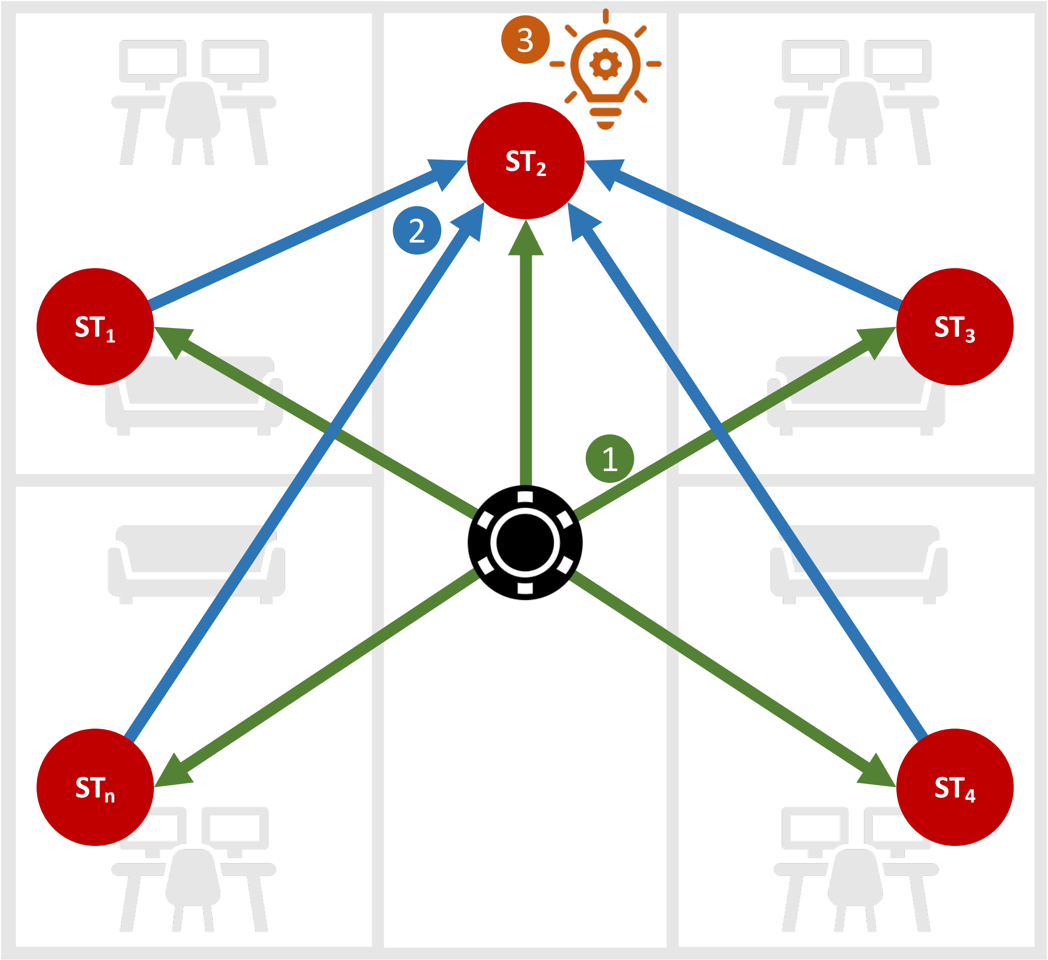


Fingerprinting

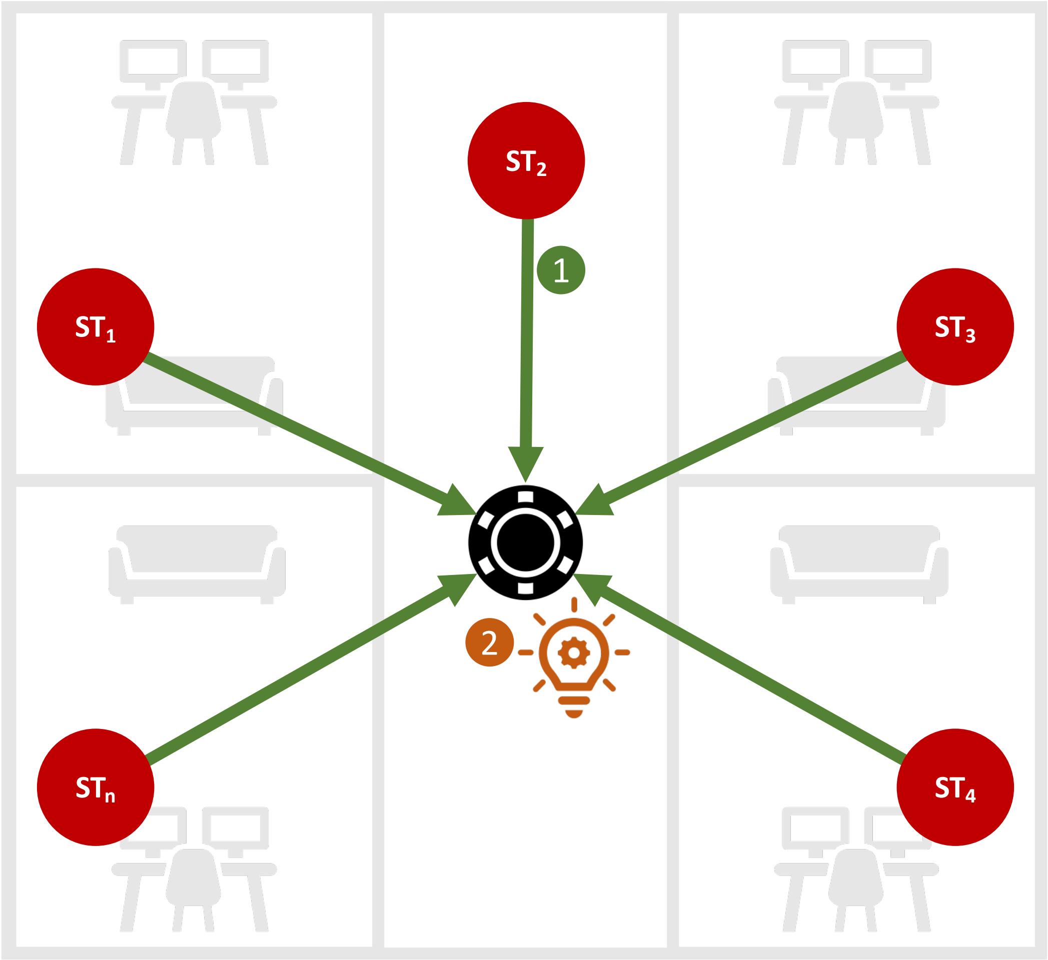




Who’s in charge?

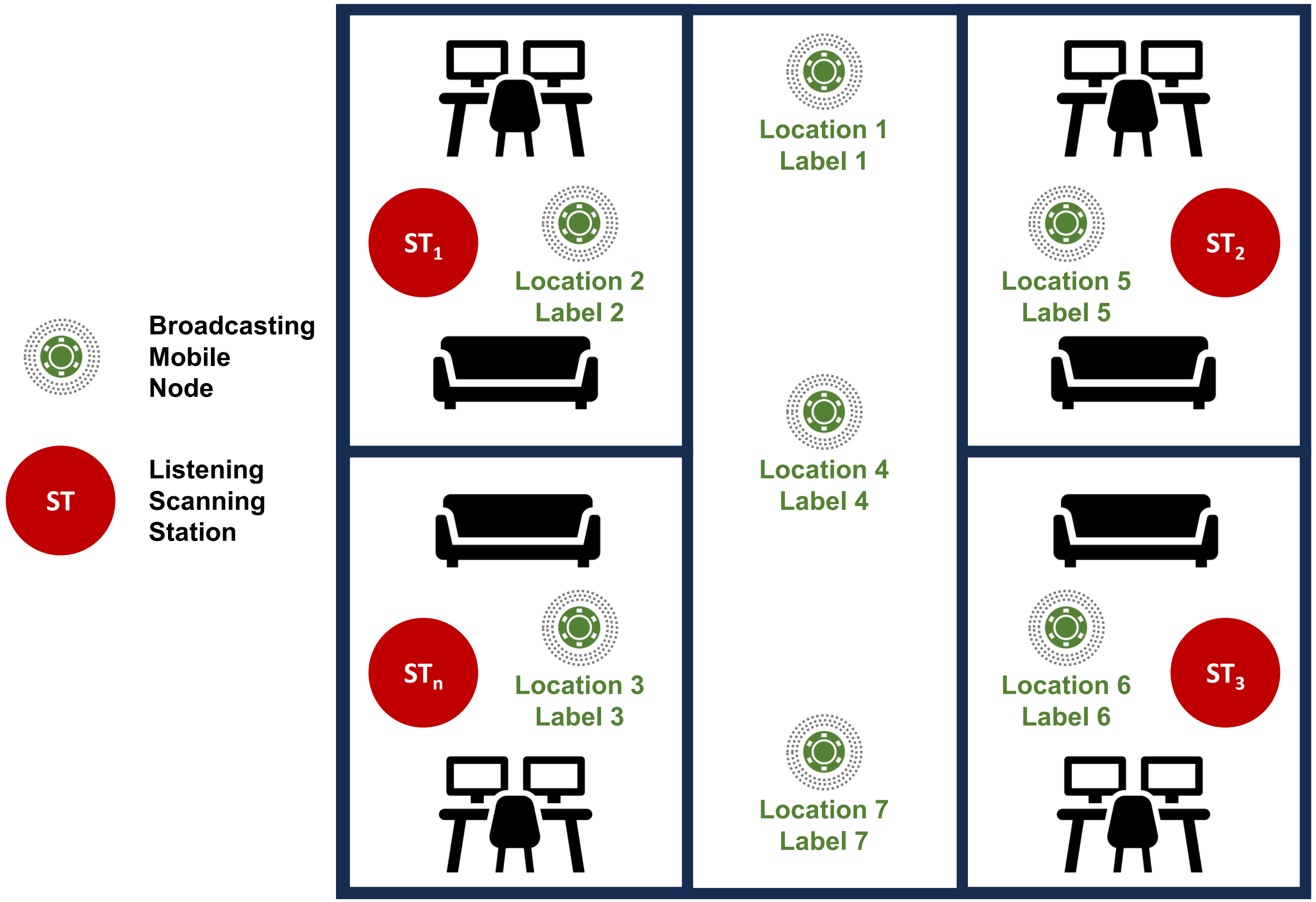


Intelligence at the Edge Infrastructure

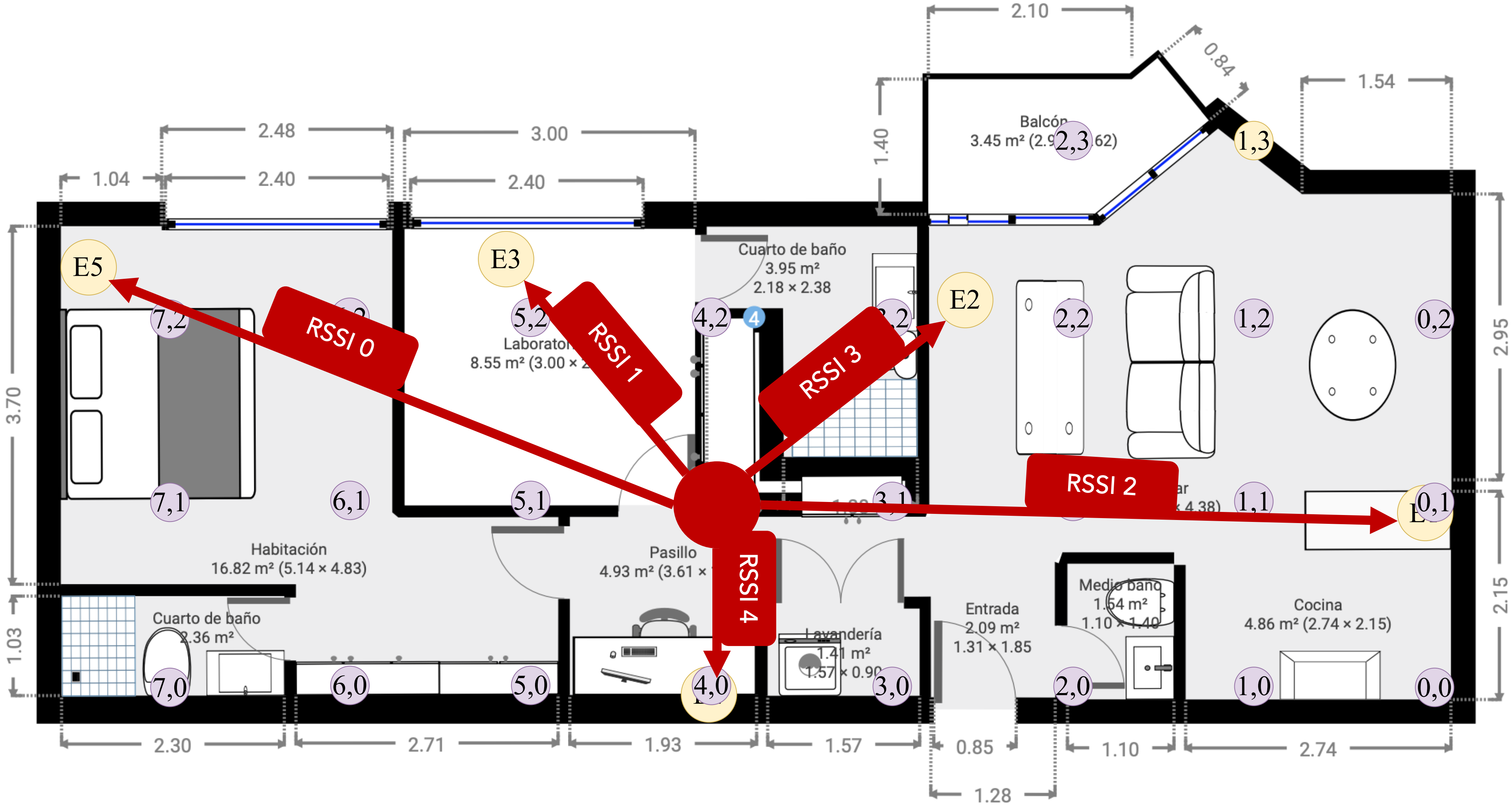


Intelligence at the Mobile Device

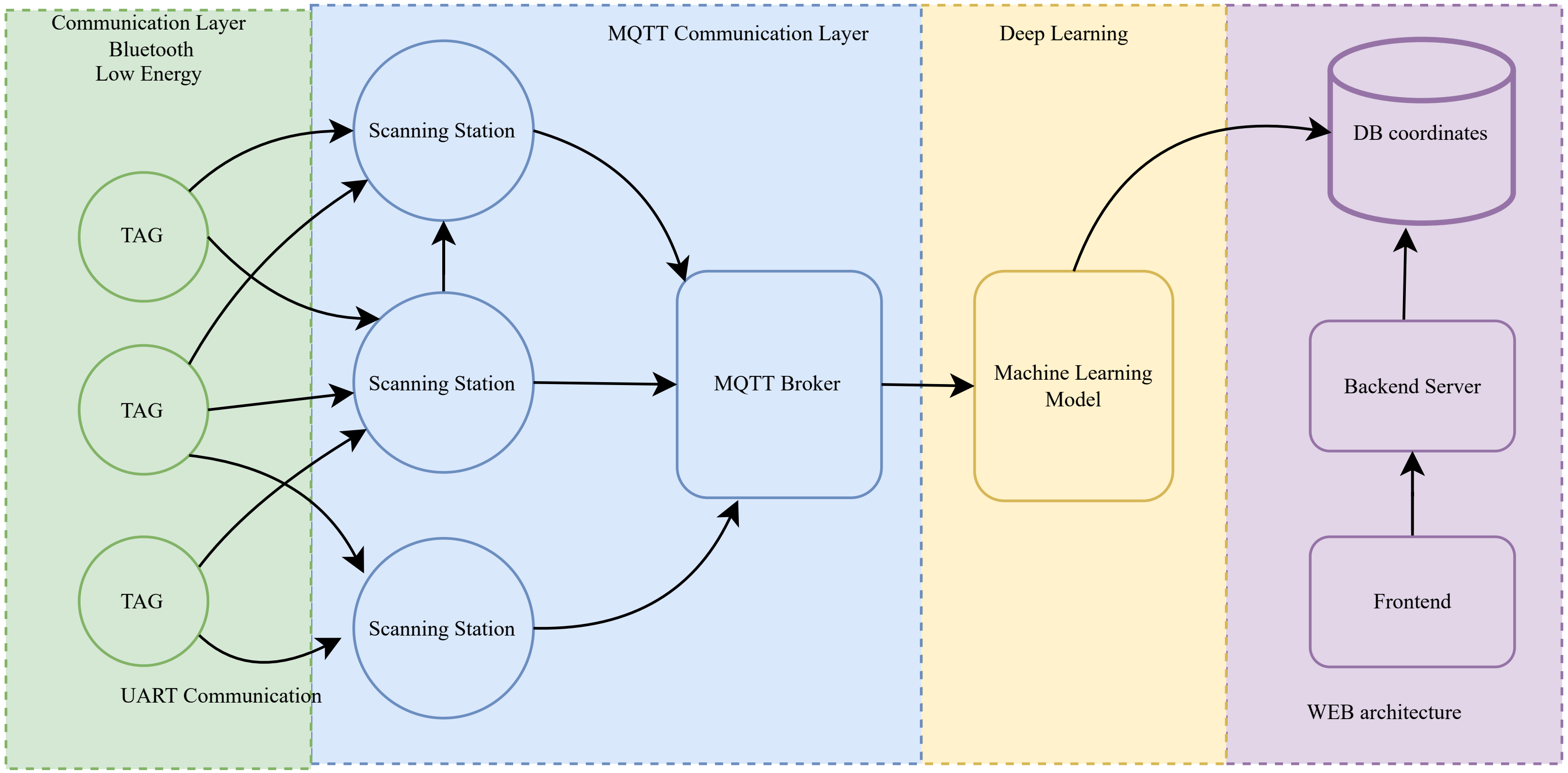
Classification Approach



Case Study 1: Apartment + RSSI



Proposed Solution (Edge Infrastructure)



TAG
BLE-enable CC2541-based
HM10 Module

Scanning Station
ESP32 and ESP82266 modules
Dual, BLE and WiFi enabled

Broker
WiFi enabled Raspberry Pi SBC
Neural Network Model

Cloud Based
Frontend and Backend

Hardware and Firmware

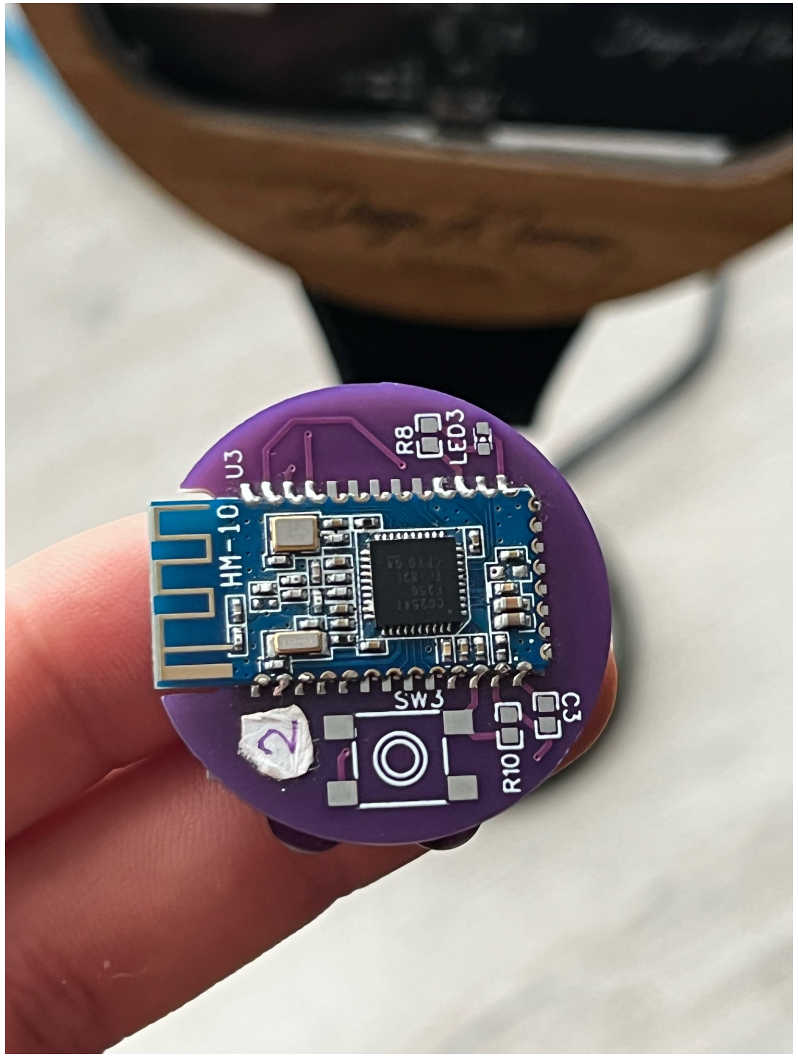
Scanning Stations

- ESP32 and ESP8266 -based
- BLE and WiFi communication
- In-board serial communication
- <5s scanning interval
- MQTT-based information centralization
- Battery power backup
- On-board display to show the available TAGs in range

Hardware and Firmware

Tracking TAGs

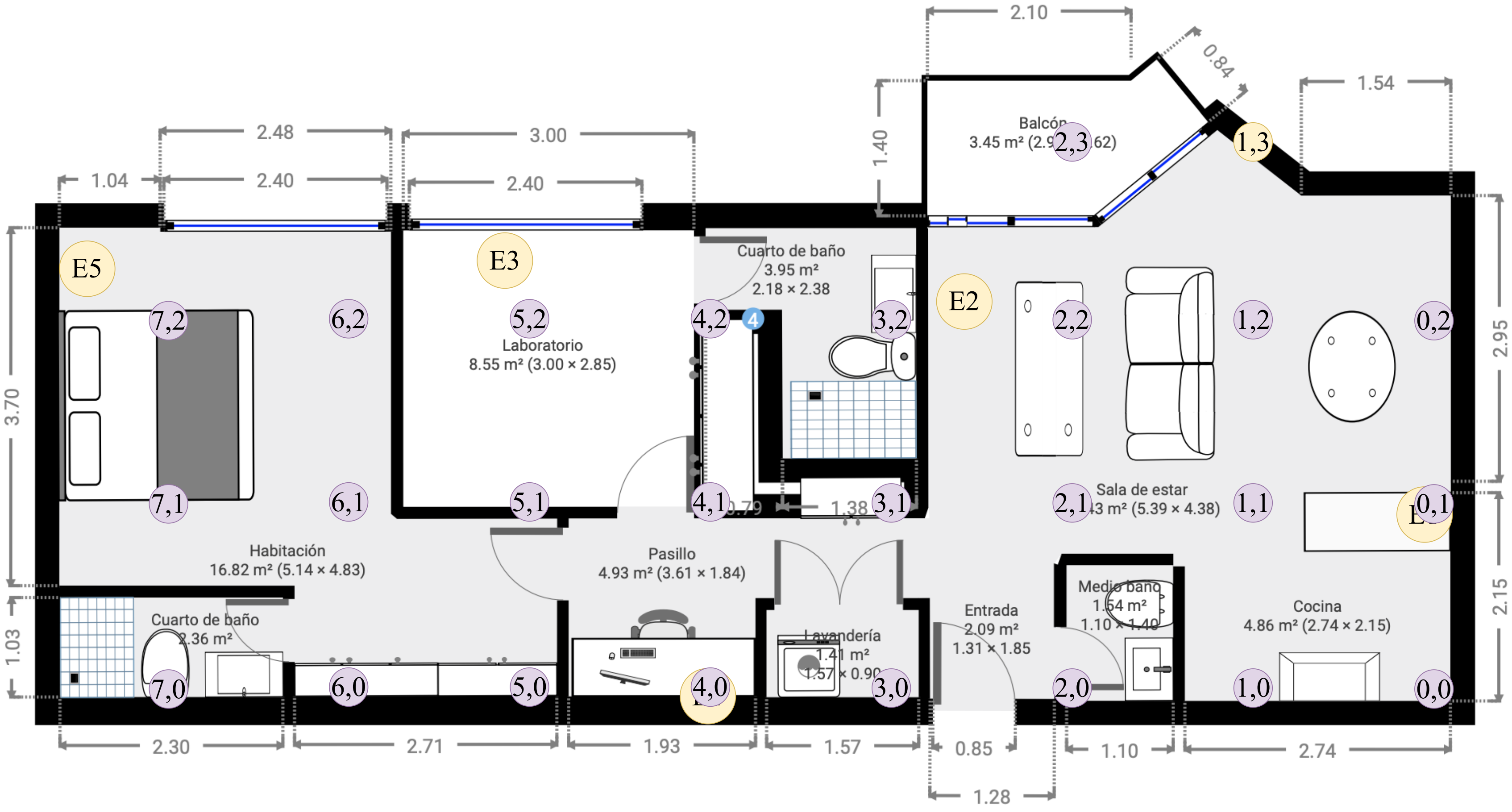
- HM-10 (TI CC2541)
- BLE advertisement
- Low power consumption (CR1616 battery)
- 500ms beacon message Interval



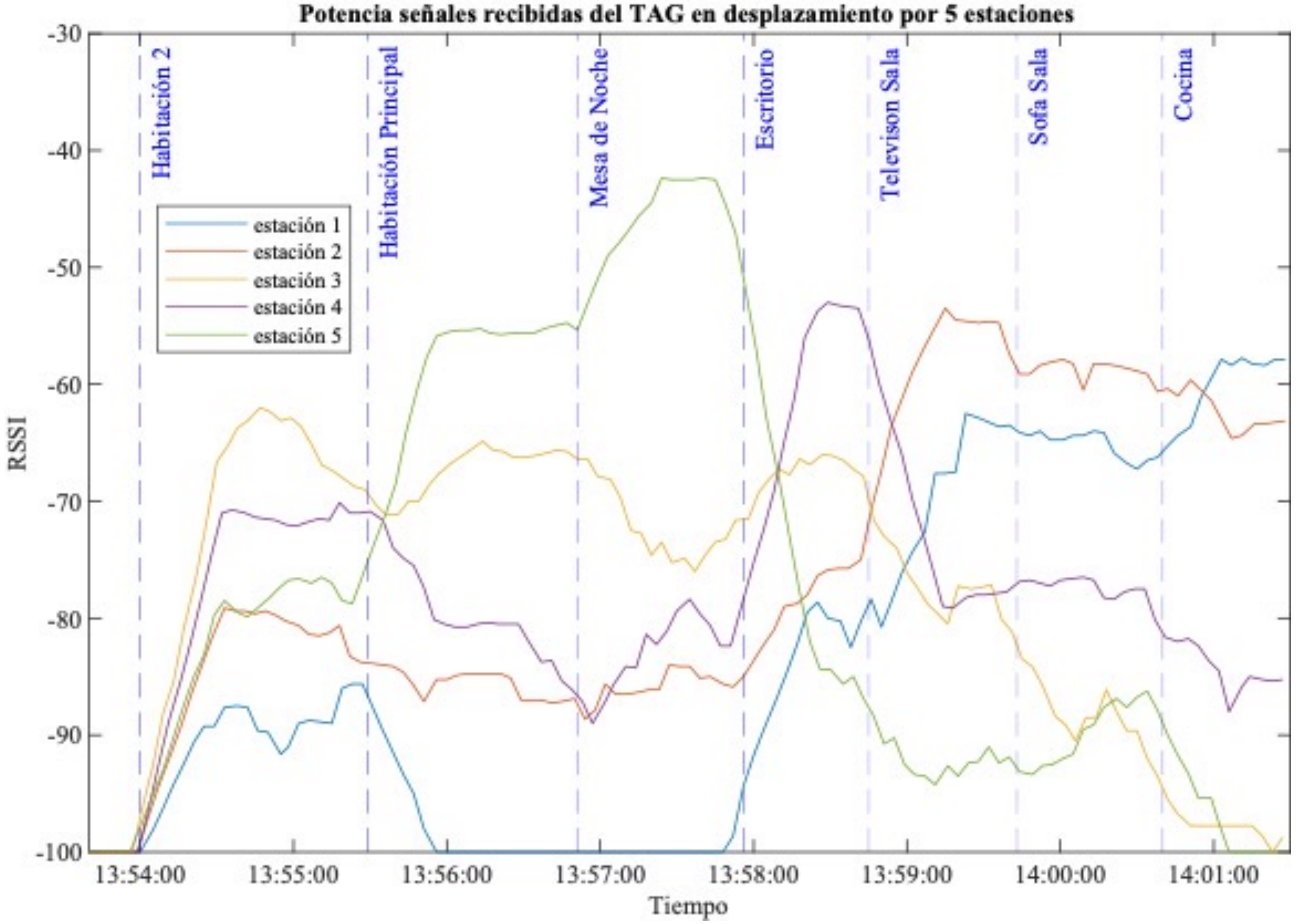
System Integration

Test Scenario

- 5 scanning stations located in a controlled environment.
- Data acquisition in predefined coordinates
- Observe and analyze the behavior of the signals
- Model training
- Performance evaluation



Behavior of the Acquired Signals



Lab	Bedroom	Bed	Study	Living	Dining
E3	E5	E5	E4	E2	E2

Recorded Position

	Approximate Coordinate	Time
Lab	5,2	13:54:00
Bedroom	6,2	13:55:29
Bed	7,2	13:56:51
Study room	4,0	13:57:56
Living room	2,2	13:58:45
Dining room	1,2	13:59:43

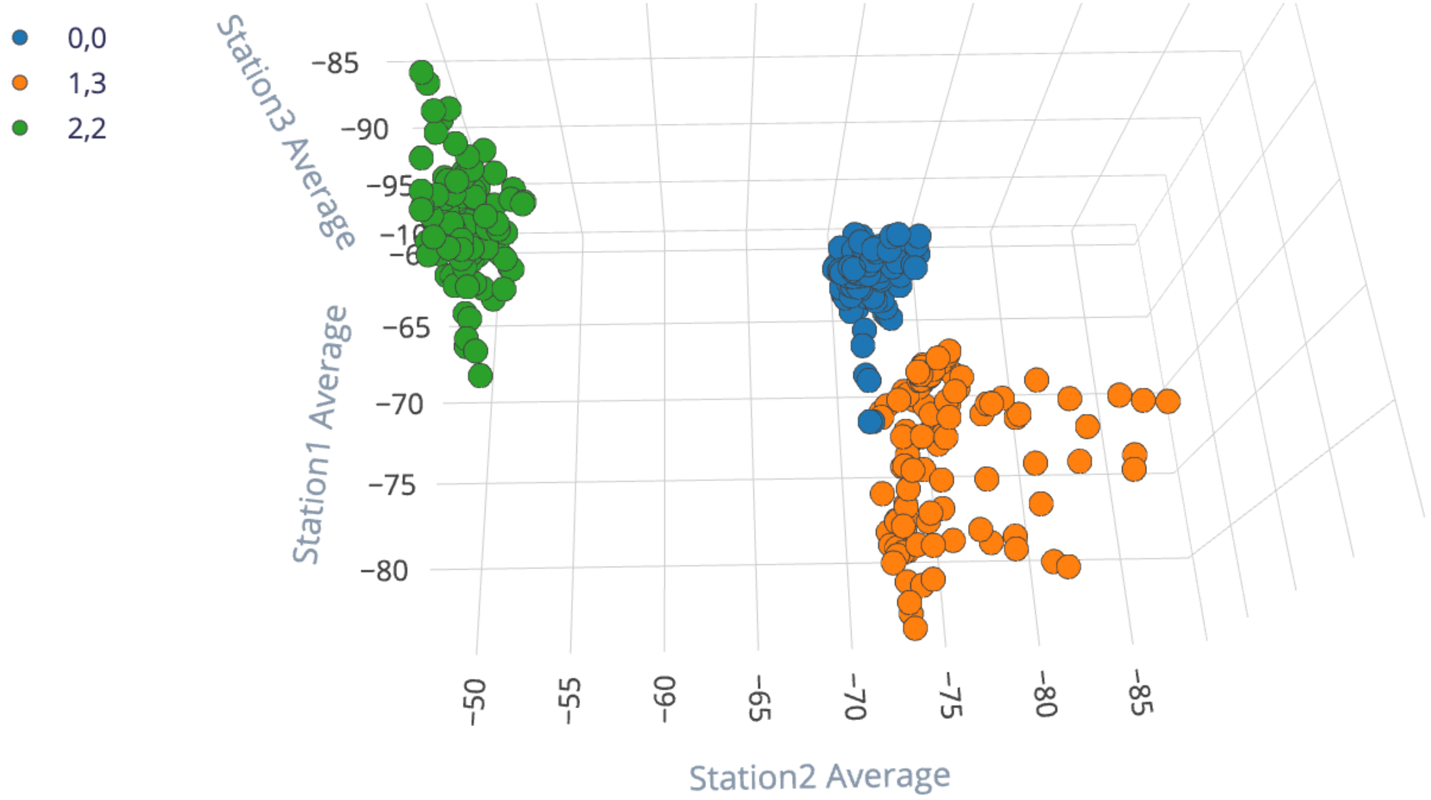
Model Training on Edge Impulse

Impulse creation

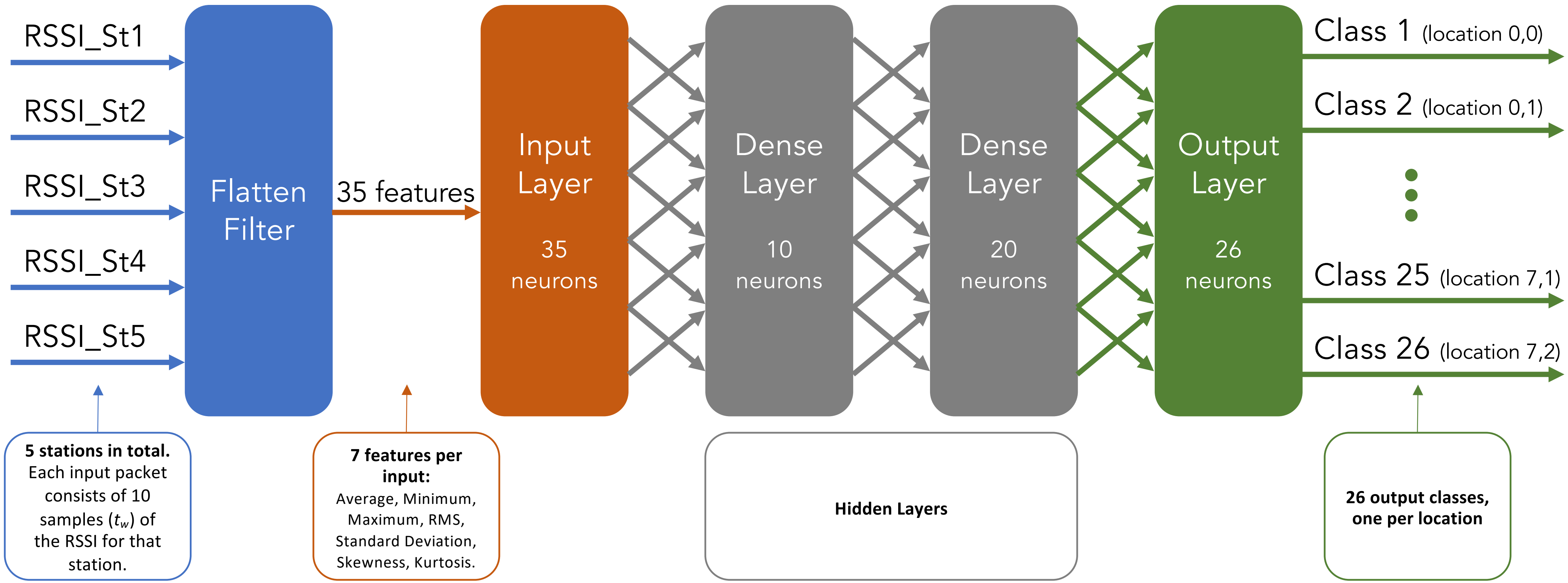
Data acquisition for only 3 locations

Feature generation

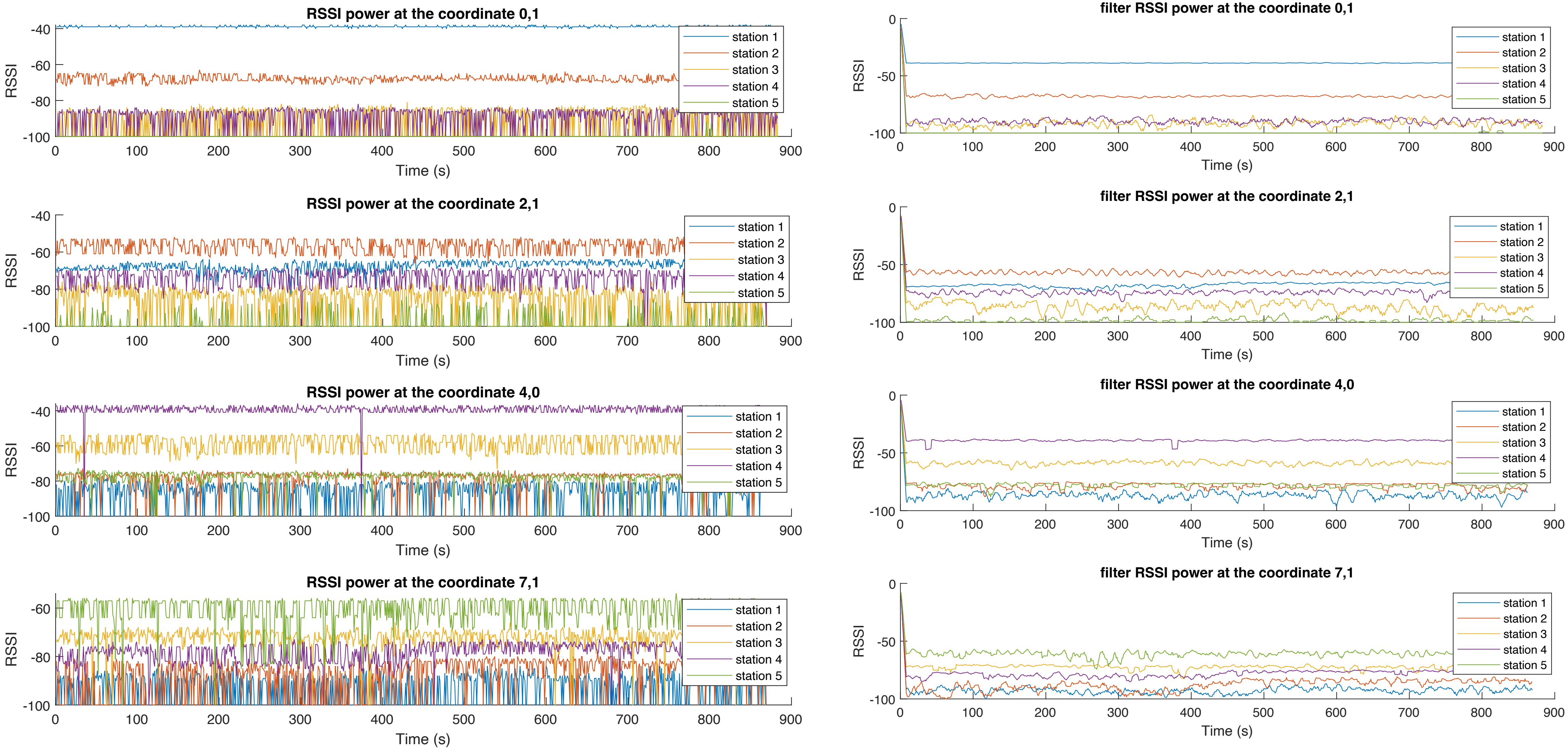
Data aggregation based on Flatten (moving average on one axis)



ANN Architecture



RSSI Signals and Pre-processing



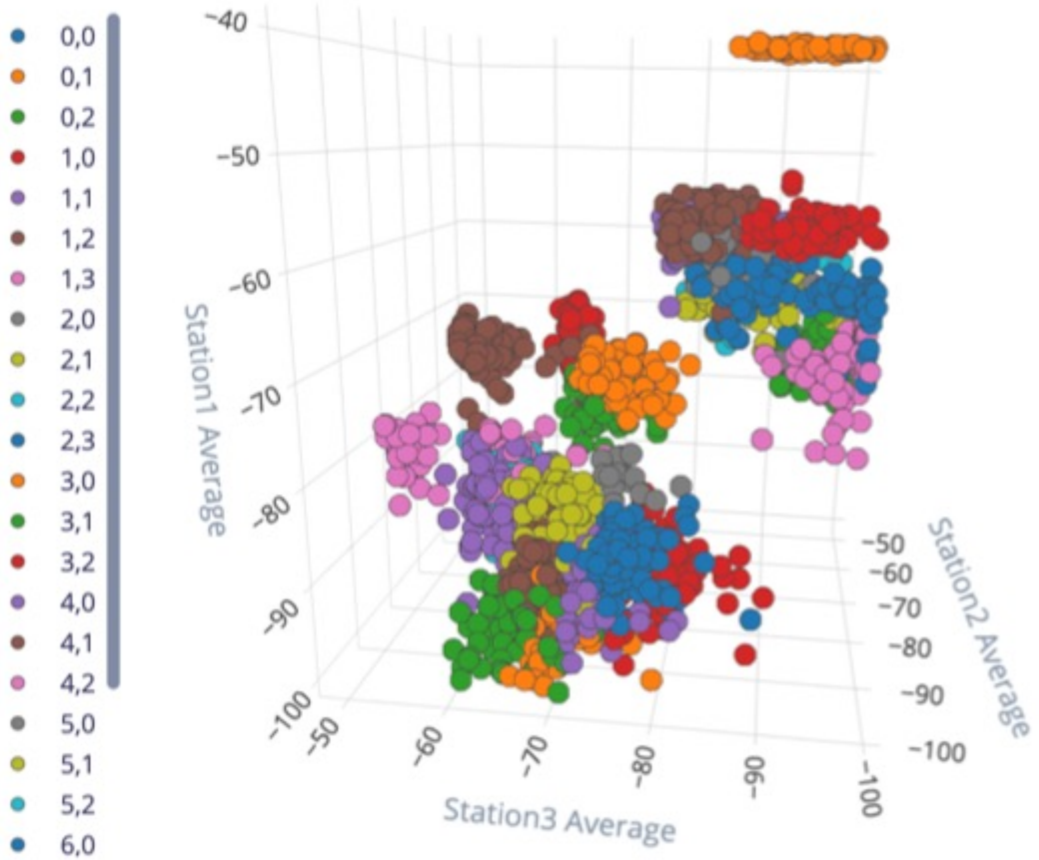
Model Training on Edge Impulse

Impulse creation

Data acquisition for 26 locations

Feature generation

Data aggregation based on Flatten (moving average on one axis)



Model Training on Edge Impulse

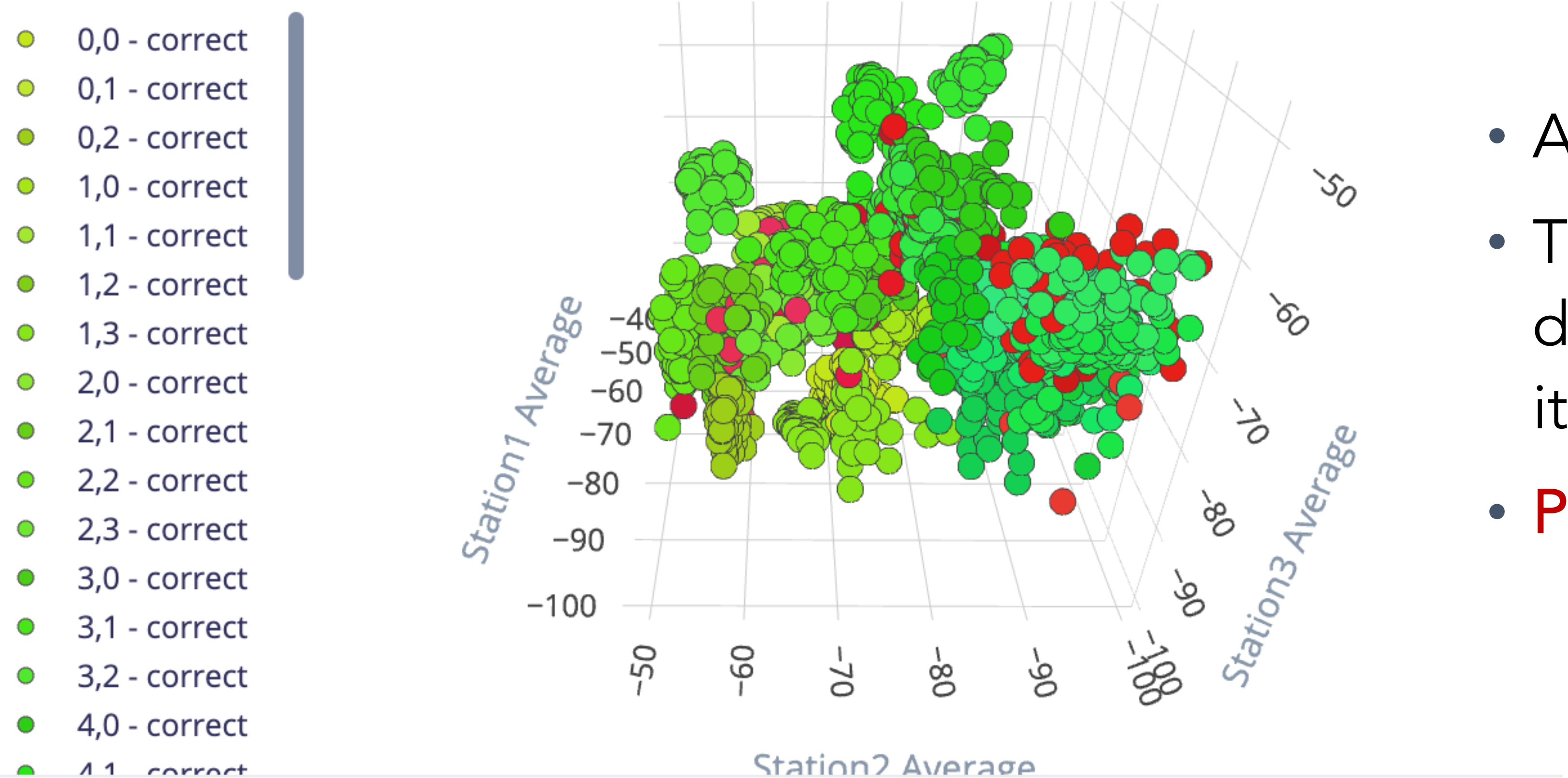
ACCURACY
94.4%

LOSS
0.11

Confusion matrix (validation set)

	0,0	1,3	2,2
0,0	99.0%	0%	1.0%
1,3	16.3%	83.7%	0%
2,2	0%	0%	100%
F1 SCORE	0.92	0.91	1.00

Model Behavior for 26 Locations



- Around 88-90% accuracy.
- The distance error is difficult to estimate since it is a classifier.
- Post-processing?

Post-Processing: Moving Median

Table 10. Estimation accuracy of TAG location in real deployment.

Location	**0,0**	**0,1**	**0,2**	**1,0**	**1,1**	**1,2**	**1,3**	**2,0**	**2,1**
Accuracy	86%	87%	87%	85%	88%	90%	89%	87%	88%
Location	**2,2**	**2,3**	**3,0**	**3,1**	**3,2**	**4,0**	**4,1**	**4,2**	**5,0**
Accuracy	86%	90%	88%	87%	85%	91%	85%	88%	86%
Location	**5,1**	**5,2**	**6,0**	**6,1**	**6,2**	**7,0**	**7,1**	**7,2**	
Accuracy	88%	88%	91%	86%	91%	87%	85%	93%	

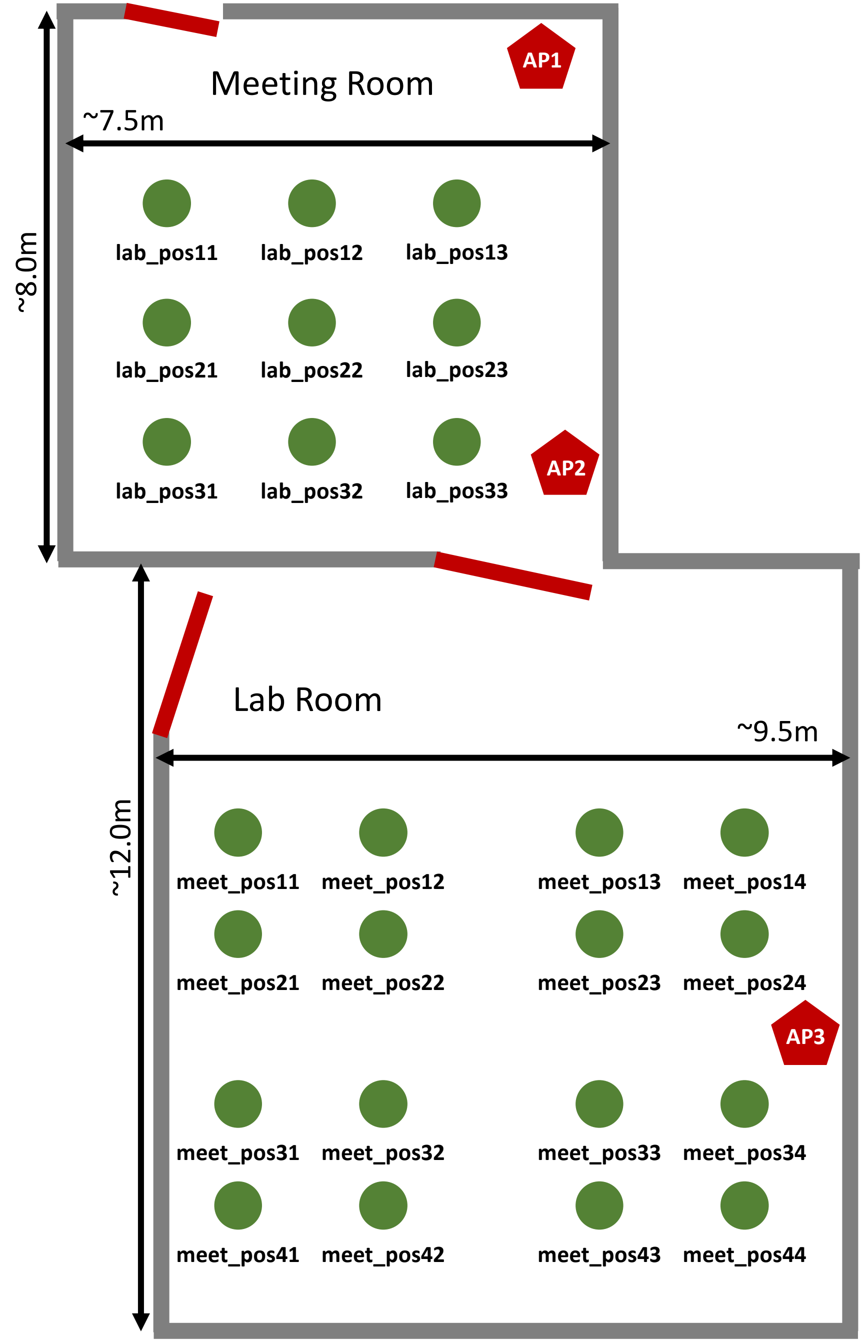
Table 11. Estimation accuracy of TAG location in real deployment after applying the post-processing stage.

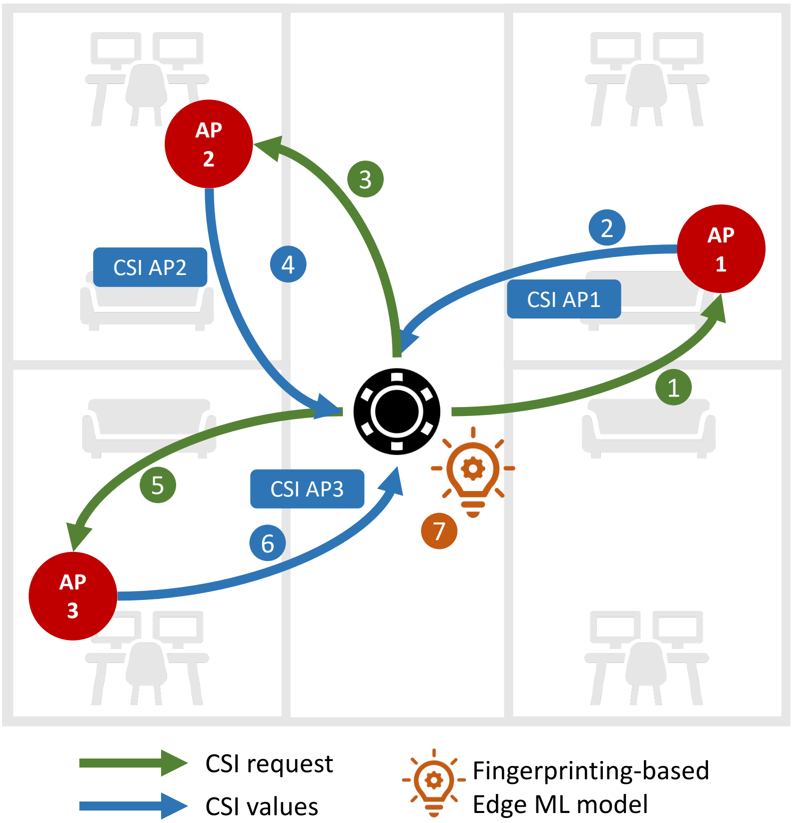
Location	**0,0**	**0,1**	**0,2**	**1,0**	**1,1**	**1,2**	**1,3**	**2,0**	**2,1**
Accuracy	93%	95%	93%	91%	95%	95%	94%	93%	95%
Location	**2,2**	**2,3**	**3,0**	**3,1**	**3,2**	**4,0**	**4,1**	**4,2**	**5,0**
Accuracy	92%	97%	93%	90%	92%	94%	89%	94%	89%
Location	**5,1**	**5,2**	**6,0**	**6,1**	**6,2**	**7,0**	**7,1**	**7,2**	
Accuracy	95%	93%	99%	94%	97%	95%	80%	97%	

88%

94%

Case Study 2: ICTP's Marconi Lab + CSI

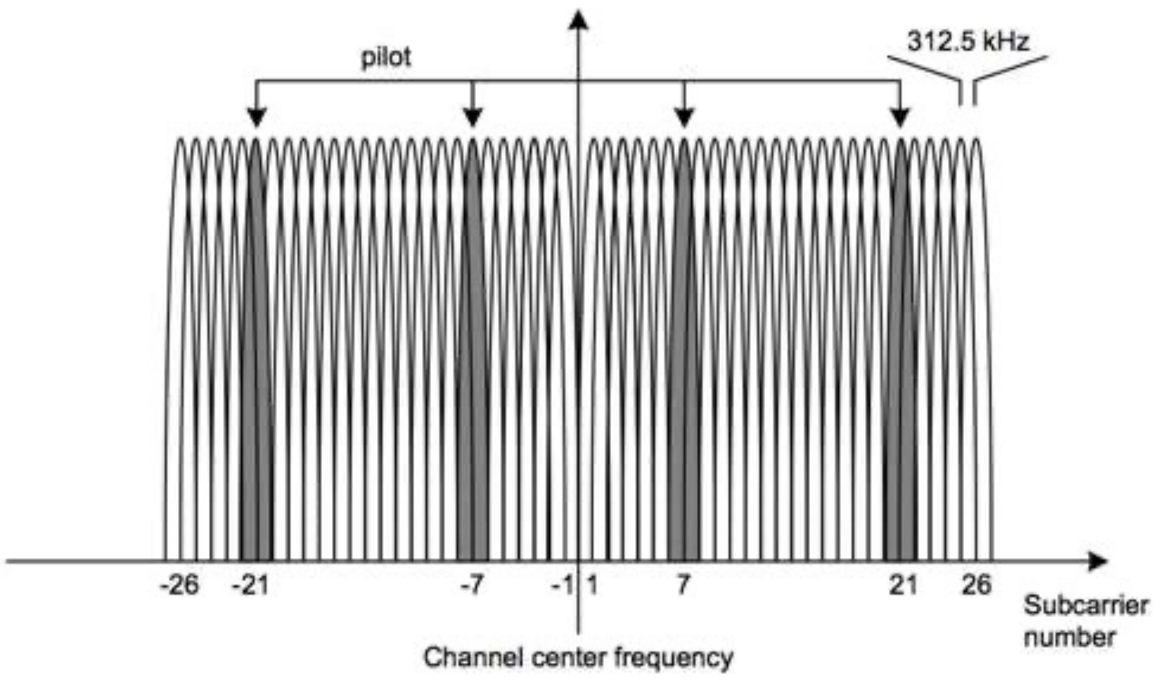




WiFi Sensing: Channel State Information

Channel State Information (CSI) is the known channel properties of a communication link. It represents the combined effect of, for example, scattering, fading, and power decay with distance.

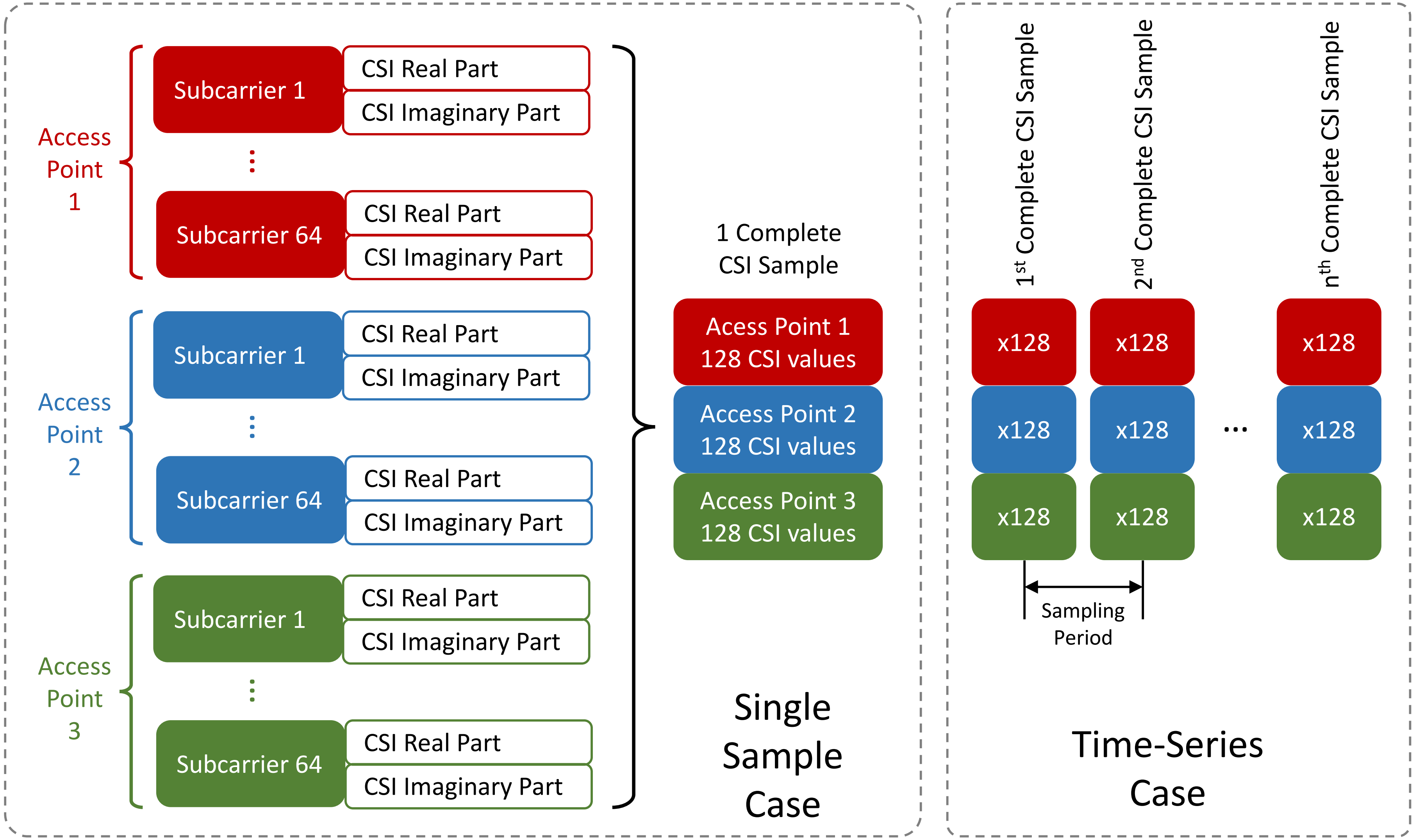
Detailed channel attributes like amplitude, phase, and frequency response are examined over time, yielding insights about the environment.



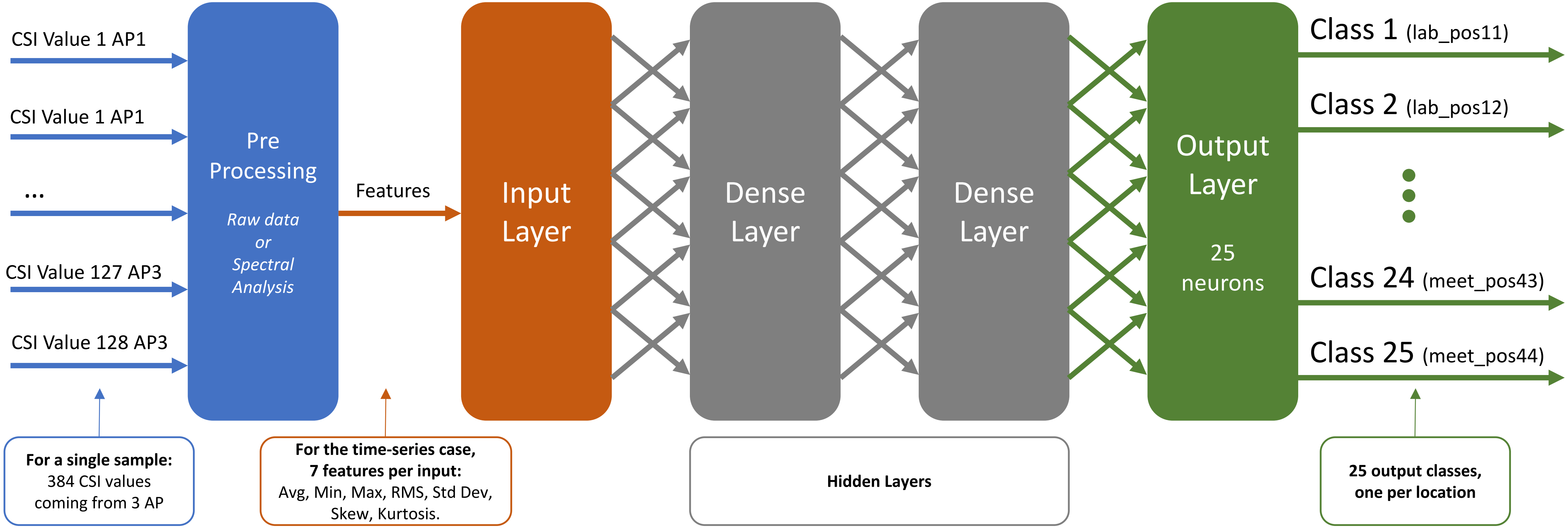
64 sub-carriers → 64 real and 64 imaginary values (128)
3 APs → 384 CSI values + 3 RSSI values = 387 values per sample

IEEE 802.11 Overview (From 11a to 11ac) – Wilus Group www.wilusgroup.com

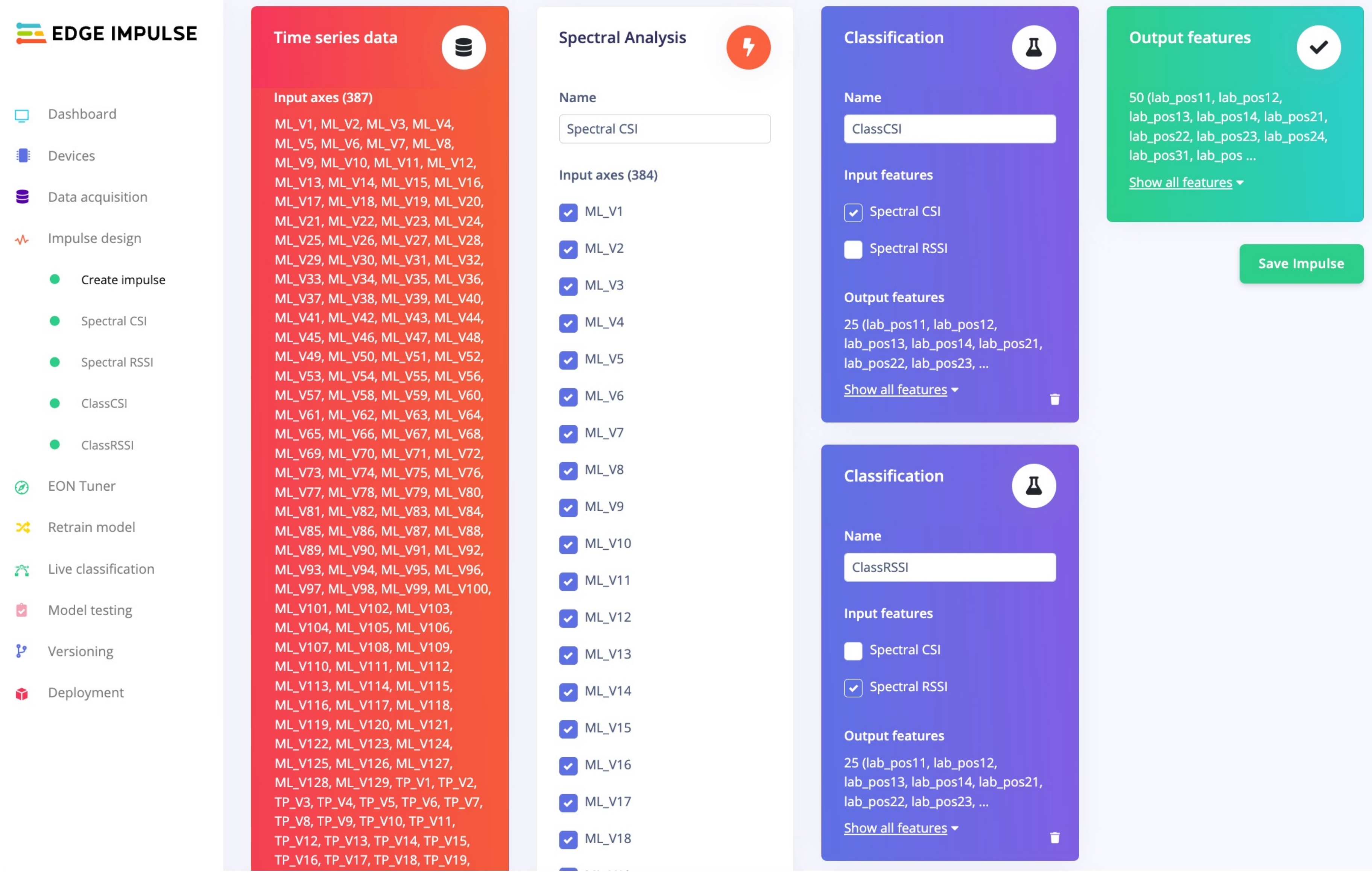
Sample Structure



ANN Architecture

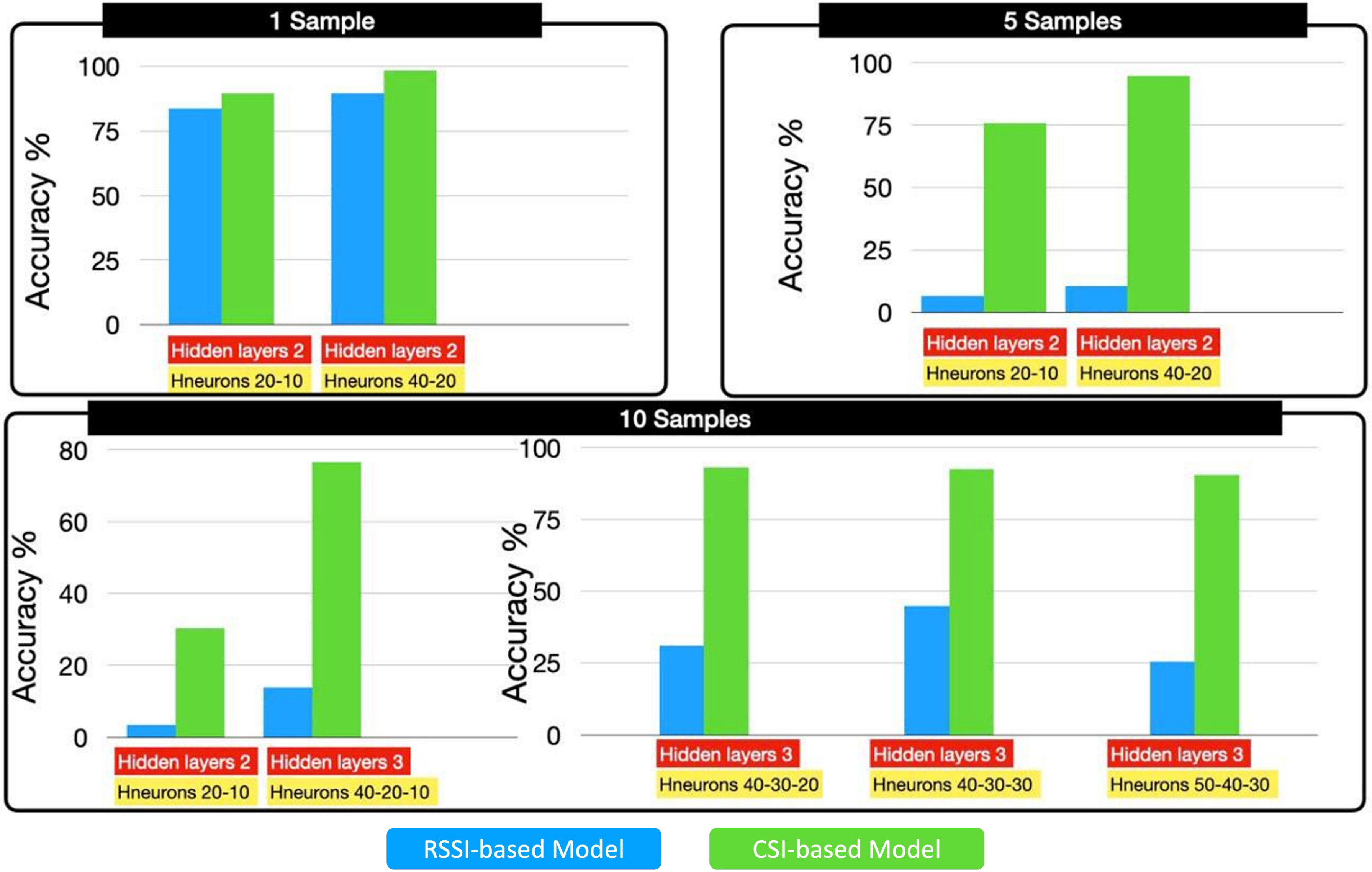


The Impulse!

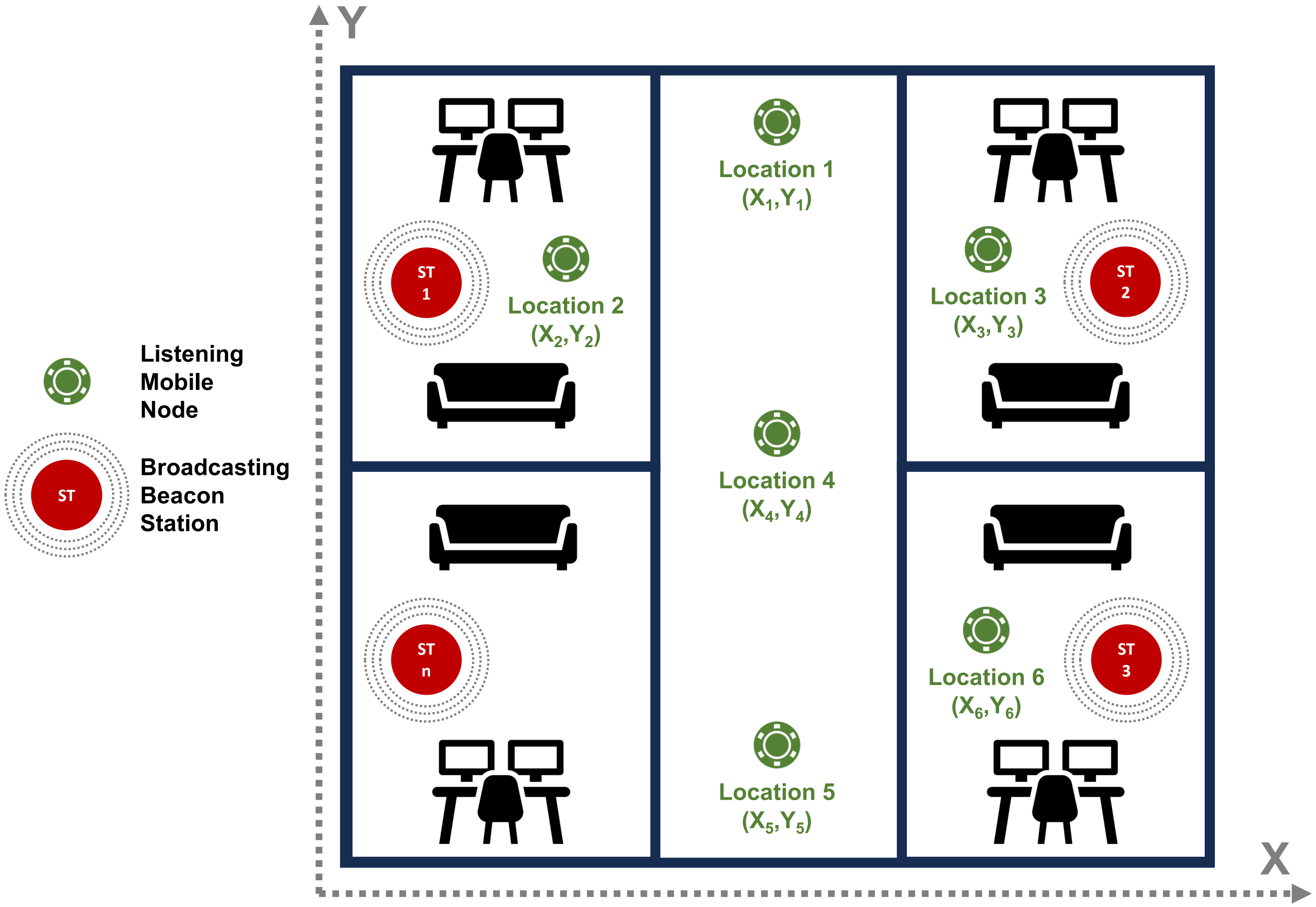


EDGE IMPULSE
Dashboard
Devices
Data acquisition
Impulse design
Create impulse
Spectral CSI
Spectral RSSI
ClassCSI
ClassRSSI
EON Tuner
Retrain model
Live classification
Model testing
Versioning
Deployment
Time series data
Input axes (387)
ML_V1, ML_V2, ML_V3, ML_V4, ML_V5, ML_V6, ML_V7, ML_V8, ML_V9, ML_V10, ML_V11, ML_V12, ML_V13, ML_V14, ML_V15, ML_V16, ML_V17, ML_V18, ML_V19, ML_V20, ML_V21, ML_V22, ML_V23, ML_V24, ML_V25, ML_V26, ML_V27, ML_V28, ML_V29, ML_V30, ML_V31, ML_V32, ML_V33, ML_V34, ML_V35, ML_V36, ML_V37, ML_V38, ML_V39, ML_V40, ML_V41, ML_V42, ML_V43, ML_V44, ML_V45, ML_V46, ML_V47, ML_V48, ML_V49, ML_V50, ML_V51, ML_V52, ML_V53, ML_V54, ML_V55, ML_V56, ML_V57, ML_V58, ML_V59, ML_V60, ML_V61, ML_V62, ML_V63, ML_V64, ML_V65, ML_V66, ML_V67, ML_V68, ML_V69, ML_V70, ML_V71, ML_V72, ML_V73, ML_V74, ML_V75, ML_V76, ML_V77, ML_V78, ML_V79, ML_V80, ML_V81, ML_V82, ML_V83, ML_V84, ML_V85, ML_V86, ML_V87, ML_V88, ML_V89, ML_V90, ML_V91, ML_V92, ML_V93, ML_V94, ML_V95, ML_V96, ML_V97, ML_V98, ML_V99, ML_V100, ML_V101, ML_V102, ML_V103, ML_V104, ML_V105, ML_V106, ML_V107, ML_V108, ML_V109, ML_V110, ML_V111, ML_V112, ML_V113, ML_V114, ML_V115, ML_V116, ML_V117, ML_V118, ML_V119, ML_V120, ML_V121, ML_V122, ML_V123, ML_V124, ML_V125, ML_V126, ML_V127, ML_V128, ML_V129, TP_V1, TP_V2, TP_V3, TP_V4, TP_V5, TP_V6, TP_V7, TP_V8, TP_V9, TP_V10, TP_V11, TP_V12, TP_V13, TP_V14, TP_V15, TP_V16, TP_V17, TP_V18, TP_V19,
Spectral Analysis
Name
Spectral CSI
Input axes (384)
ML_V1
ML_V2
ML_V3
ML_V4
ML_V5
ML_V6
ML_V7
ML_V8
ML_V9
ML_V10
ML_V11
ML_V12
ML_V13
ML_V14
ML_V15
ML_V16
ML_V17
ML_V18
Classification
Name
ClassCSI
Input features
Spectral CSI
Spectral RSSI
Output features
25 (lab_pos11, lab_pos12, lab_pos13, lab_pos14, lab_pos21, lab_pos22, lab_pos23, ...
Show all features
Classification
Name
ClassRSSI
Input features
Spectral CSI
Spectral RSSI
Output features
25 (lab_pos11, lab_pos12, lab_pos13, lab_pos14, lab_pos21, lab_pos22, lab_pos23, ...
Show all features
Output features
50 (lab_pos11, lab_pos12, lab_pos13, lab_pos14, lab_pos21, lab_pos22, lab_pos23, lab_pos24, lab_pos31, lab_pos ...
Show all features
Save Impulse

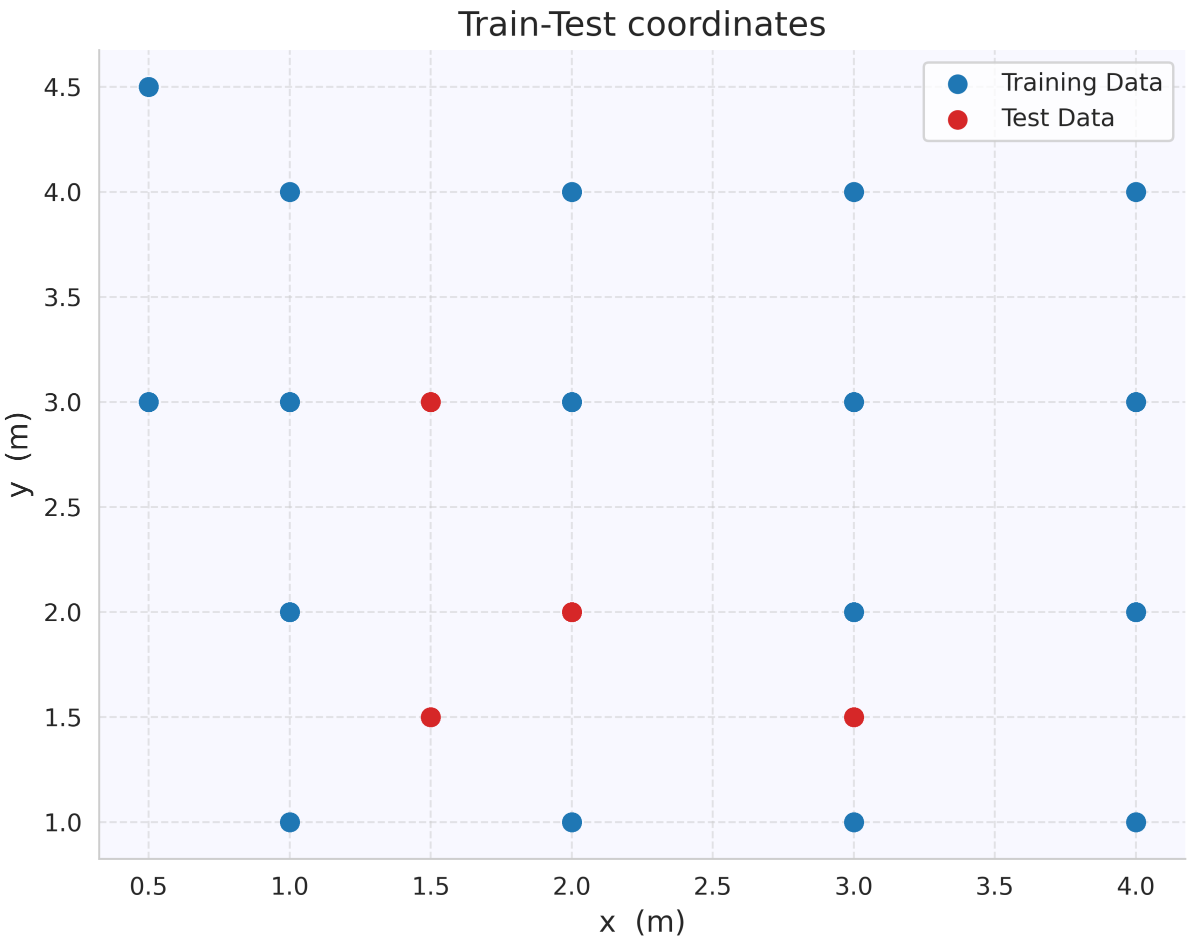
CSI vs RSSI


1 Sample
Accuracy %
100
75
50
25
0
Hidden layers 2
Hneurons 20-10
Hidden layers 2
Hneurons 40-20
5 Samples
Accuracy %
100
75
50
25
0
Hidden layers 2
Hneurons 20-10
Hidden layers 2
Hneurons 40-20
10 Samples
Accuracy %
80
60
40
20
0
Hidden layers 2
Hneurons 20-10
Hidden layers 3
Hneurons 40-20-10
Accuracy %
100
75
50
25
0
Hidden layers 3
Hneurons 40-30-20
Hidden layers 3
Hneurons 40-30-30
Hidden layers 3
Hneurons 50-40-30
RSSI-based Model
CSI-based Model

How about a Regression Approach?



Error in meters!



Regressors Errors:

- Linear: 0.63 m
- Decision Tree: 0.81 m
- Random Forest: 0.73 m
- XGBoost: 0.95 m
- Artificial NN: 0.62 m
- GRU: 0.58 m

Some of our papers:

- AVELLANEDA, Diego; **MENDEZ, Diego**; FORTINO, Giancarlo. BLE-based Indoor Positioning Platform Utilizing Edge Tiny Machine Learning. IEEE Intl Conf on Pervasive Intelligence and Computing. September 2022. ISBN: 978-1-6654-6297-6. DOI: 10.1109/DASC/PiCom/CBDCom/Cy55231.2022.9927866.
- AVELLANEDA, Diego; **MENDEZ, Diego**; FORTINO, Giancarlo. A TinyML Deep Learning Approach for Indoor Tracking of Assets. Sensors. MDPI. January 2023. Volume 23, Issue 3, 1542. ISSN: 1424-8220. DOI: 10.3390/s23031542.
- **MÉNDEZ, Diego**; **ZENNARO, Marco**; ALTAYEB, Moez; MANZONI, Pietro. On TinyML WiFi Fingerprinting-Based Indoor Localization: Comparing RSSI vs. CSI Utilization. 2024 IEEE 21st Consumer Communications & Networking Conference (CCNC), Las Vegas, NV, USA, 2024, pp. 1-6. eISBN: 979-8-3503-0457-2. DOI: 10.1109/CCNC51664.2024.10454828.
- **MENDEZ, Diego**; CROVO, Daniel; AVELLANEDA, Diego. Book chapter: Machine Learning Techniques for Indoor Localization on Edge Devices. Book: TinyML for Edge Intelligence in IoT and LPWAN Networks. Editors: Marco Zennaro and Bharat Chaudhari. Elsevier. ISBN: 9780443222030.

Thank you!

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