

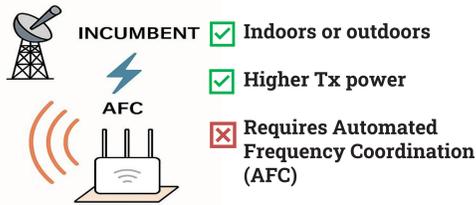
Indoor/Outdoor Spectrum Sharing Enabled by GNSS-based Classifiers

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Indoor/Outdoor Classification Importance

- Modern spectrum-sharing policies heavily depend on accurately identifying the indoor/outdoor (I/O) environment of devices.
- Example:** to address spectrum congestion in the mid-band (1–10 GHz) range, the FCC opened the 6 GHz band for unlicensed use by devices such as Wi-Fi 6E. To protect licensed outdoor incumbents—providing critical services such as fixed microwave links—the FCC established two main operational modes for unlicensed devices:

Standard Power (SP)

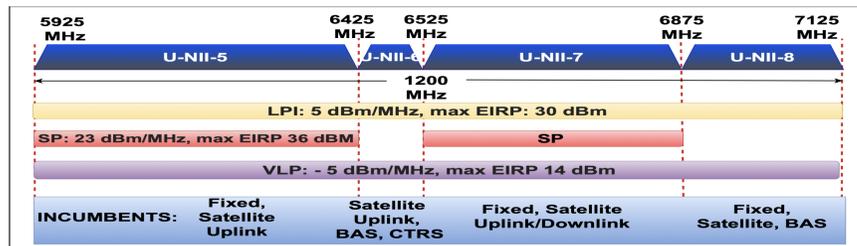


- Indoors or outdoors
- Higher Tx power
- Requires Automated Frequency Coordination (AFC)
- Access to only U-NII 5 and U-NII 7 sub-bands

Low Power Indoor (LPI)



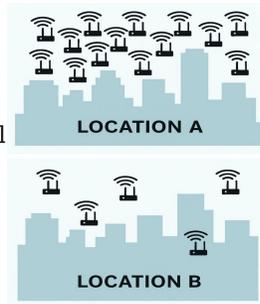
- Only indoors
- Low Tx power
- Access to all channels



- Issue:** how to determine I/O environment of a device?
- To restrict indoor usage, LPI APs must have **only integrated antennas, no battery-power, and no weatherization.**
- These LPI limitations are restrictive and inefficient: **there is a need for robust Indoor/Outdoor (I/O) classification.**

Previous Approaches & Our Idea

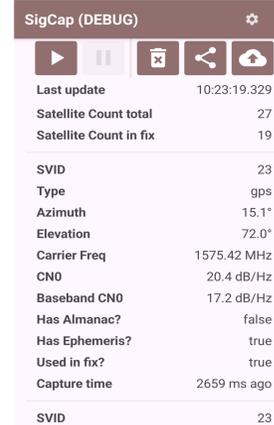
- Previous work:
 - Using Wi-Fi and cellular information: they depend on local infrastructure → not generalizable
 - Temperature and movement sensors → not useful in the context of spectrum sharing
 - Static data in only one location → not real-time and generalizable
- Our Idea: GNSS satellite data:



- Available everywhere
- Not dependent on local infrastructure
- Cheap and ubiquitous sensors
- Relevant to the concept of spectrum sharing

Dataset: Tools & Collection

- We utilized **raw GNSS features captured in SigCap app in smartphones** as a proof-of-concept in dynamic environments
- We collected a diverse dataset within USA and abroad, in a variety of environments, e.g., basements, airports near glass windows, open areas, and driving under bridges.
- Multiple phone models to reduce bias, e.g., Google Pixel 5, Pixel 6, Pixel 8, Samsung S21 Ultra, S22+, S24+.



Scan For Demo Video!



How Does GNSS Data Work?

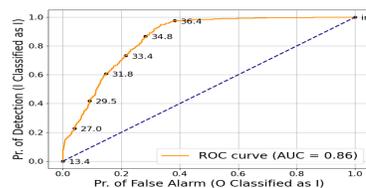
Two determining factors:

a) CNR Level

- Signal attenuation
- Indoors: fewer satellites detected, lower CNR

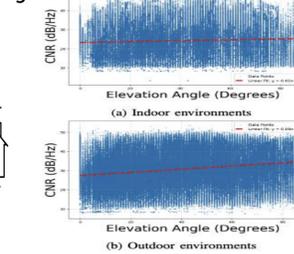
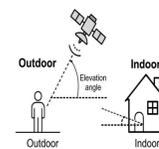


- Prob. of detection (PD) = indoor classified indoor*
- Prob. of false alarm (PF) = outdoor misclassified as indoor*
- Example: BeiDou, 26, 1574 MHz*



b) Elevation Angle

- Outdoor: stronger signals at high elevation angles
- Indoor: ceilings/walls attenuate vertical signals



Threshold (dB/Hz)	13	27	30	32	33	35	36
PD(%)	0	21	41	61	70	90	99
PF(%)	0	5	10	18	20	29	40

Methodology & Results

Threshold-based method

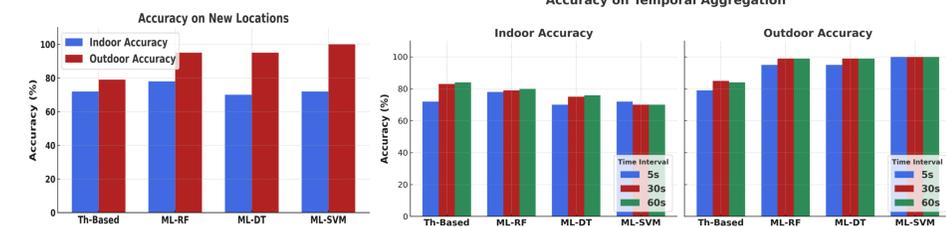
- Classifying each satellite CNR level against predefined threshold.



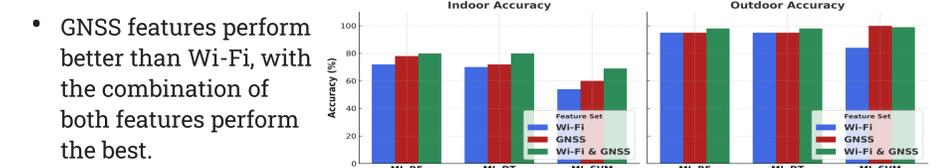
- We derive **Probability of Detection (PD)** and **Probability of False Alarm (PF)** from CNR values per satellite and calculate accuracy.
- We select **the best threshold to maximize accuracy:** values lower than threshold is predicted indoors and vice versa.
- Moreover, if the number of observed satellites is less than or equal to 10, the environment is automatically classified as indoor.

ML-based methods: Support Vector, Decision Tree, and Random Forest

- We utilized all available GNSS features (CNR, Freq., Angles, etc.) as well as average CNR and total number for all satellites.



- Indoor prediction error is higher due to the prevalence of near-window cases; removing these data increases indoor accuracy by 7-15%.
- We observe an overall increase in performance when we aggregate predictions using majority voting. Aggregating predictions over 30 seconds shows largest accuracy boost.



Containment instead of indoor/outdoor

- For indoor/outdoor spectrum sharing, **“containment”** describes electromagnetic (EM) isolation better than indoor/outdoor labels.
- There are various containment levels, e.g., **indoor near windows for “poor containment”** and **outdoor under bridges for “well contained”**.
- Table shows stronger link between GNSS features and containment levels.

Environment	Description	ML-RF, Prediction (%)
	Outdoor Well-Contained	In. = 90% Out. = 10%
	Outdoor Poorly-Contained	In. = 0% Out. = 100%
	Indoor Well-Contained	In. = 96% Out. = 4%
	Indoor Poorly-Contained	In. = 56% Out. = 44%

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