Semantic Mapping using YOLOv8, WLAN, GPS

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Introduction

- ➔ Semantic mapping is a powerful concept that enhances traditional indoor mapping by adding a layer of semantic understanding to the physical layout of spaces like objects, GPS signal and WiFi.
- ➔ It is a sophisticated concept that requires accurate object detection and understanding of spatial relationships.

Motivation

➔ Indoor localization has evolved from an advantage to an essential element in the quickly developing field of smart environments.

Problems :

Precise Navigation
Dynamic Environment Adaptation
Localization Accuracy

➔ These issues can be solved by adding semantic mapping, resulting in efficient navigation, contextual understanding, task execution, environment adaption, autonomy, adaptability, and accurate localisation.

Background

Smart Buildings and IoT Integration
Augmented Reality Navigation
Robotics and Automation

[Real-time Use]

- ➔ Recent advances in indoor localization methods that use spatial context to improve the location estimation. [1]
- ➔ Semantic localization dataset for indoor environments named ViDRILO. The dataset provides five sequences of frames acquired with a mobile robot in two similar office buildings under different lighting conditions. [2]
- ➔ Accurate Localization which enables the robot to include other types of observations in the classification, like camera images.[3]

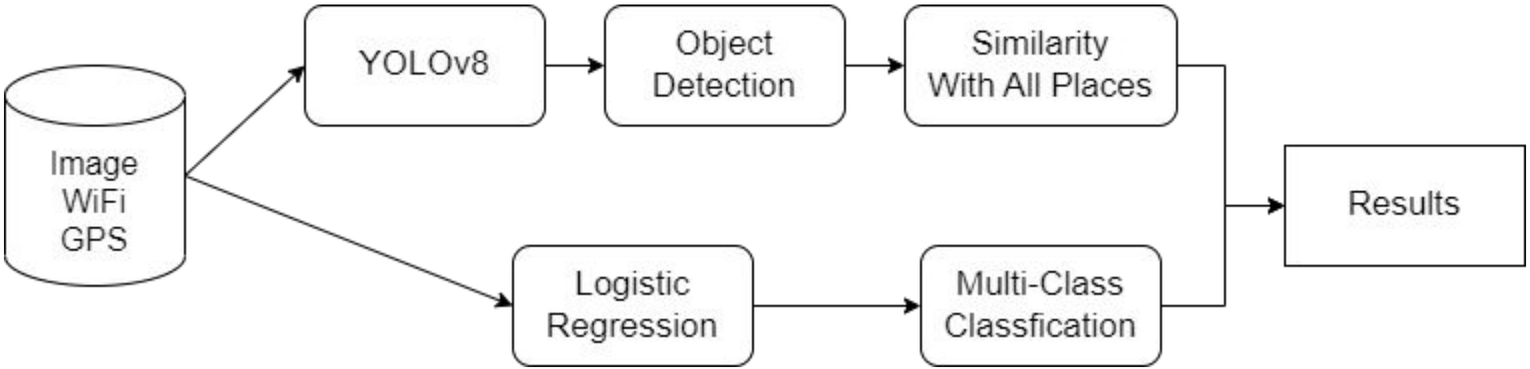
Problem Statement

How to achieve accurate semantic mapping with dynamic environment adaptation for easier navigation and localization in indoor ?

Objective

➔ Our objective is to utilize semantic mapping to enhance place classification performance by using information about objects, WiFi and GPS data.

Workflow

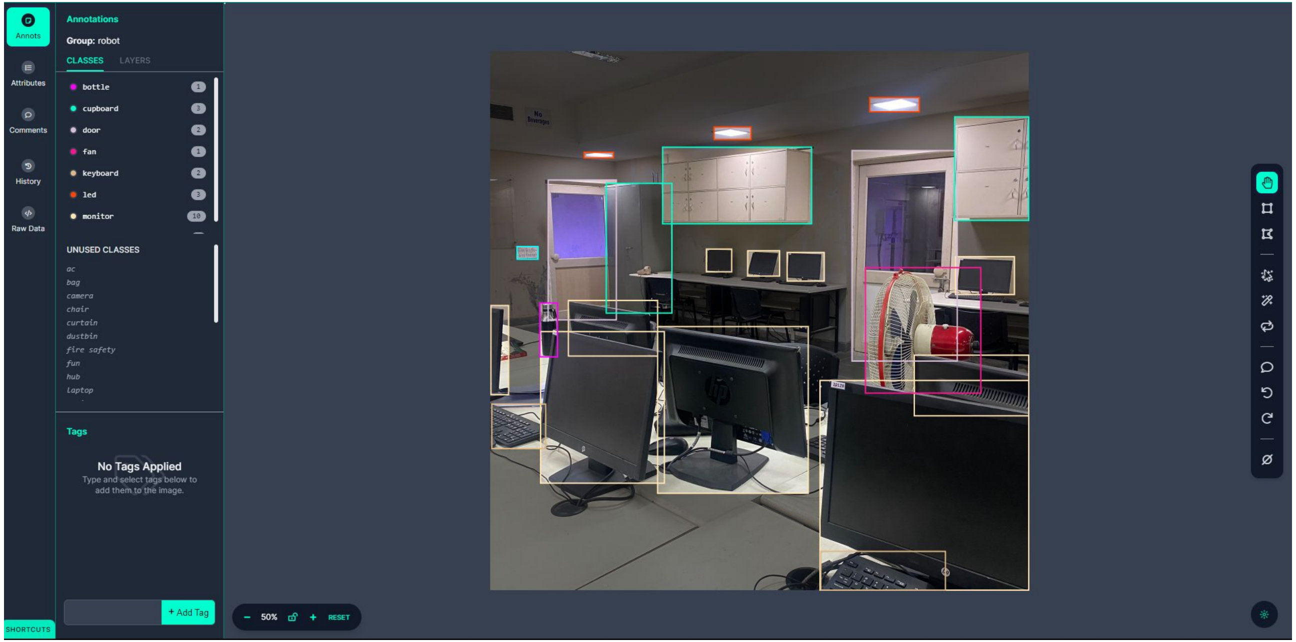


[fig1: Workflow]

YOLOv8

- ➔ Real-time object detection and image segmentation model
- ➔ YOLOv8 models for object detection ship already pre-trained on the COCO dataset, whic is a huge collection of images of 80 different types
- ➔ Annotation: It typically include the coordinates of the bounding boxes, as well as the class label associated with each object.

Custom Object Detection



[fig2:Labeling]

WiFi

- WiFi networks emit radio waves at specific frequencies.
- By analyzing the distribution of WiFi signal strengths across an indoor space, it’s possible to gain insights about Environment.
- WiFi signals interact with walls, furniture, and other objects, leading to variations in signal strength across different locations.

GPS

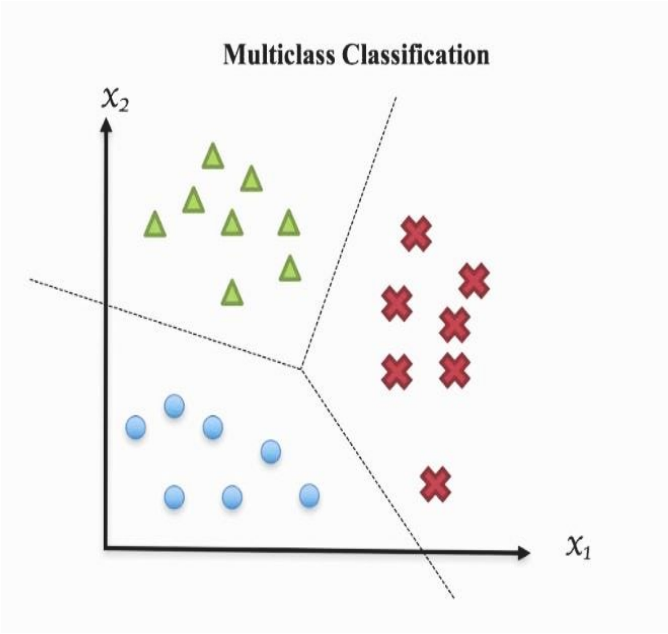
➔ Global Positioning System (GPS) signals, originally designed for outdoor navigation, can still provide valuable context for indoor localization projects, despite their limitations within enclosed spaces.

➔ **Problems:**

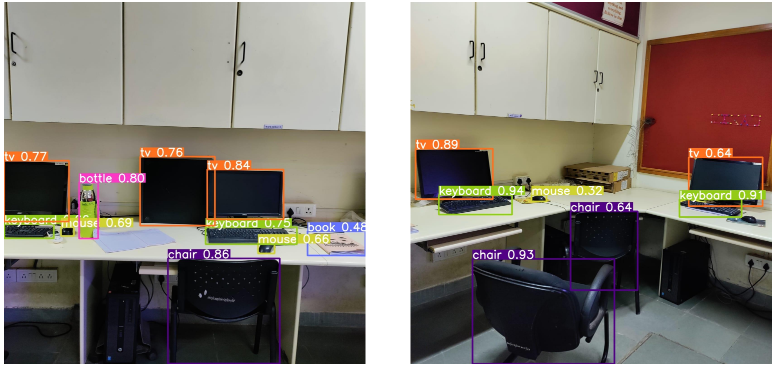
1. Weak Signals
2. Multipath Effects
3. Coarse Accuracy

Logistic Regression

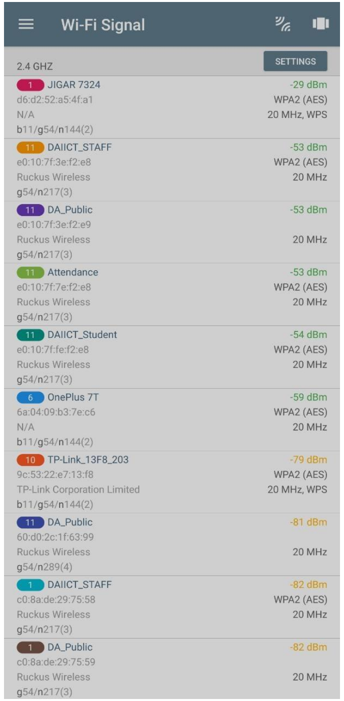
- ➔ Binary Classification Task.
- ➔ Training Multiple Classifiers(**One-vs-All**): For each room in your dataset, train a separate Logistic Regression classifier each focusing on distinguishing a particular room.
- ➔ When predicting the room for a given WiFi and GPS data point, We run the input through each of the trained classifiers. The classifier with the highest predicted probability indicates the most likely room.



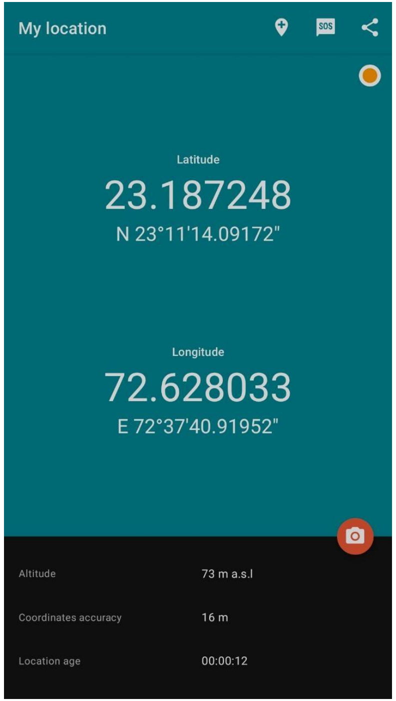
Data Collection



[fig3:YOLOv8 Object Detection]



[fig4:WiFi Data]



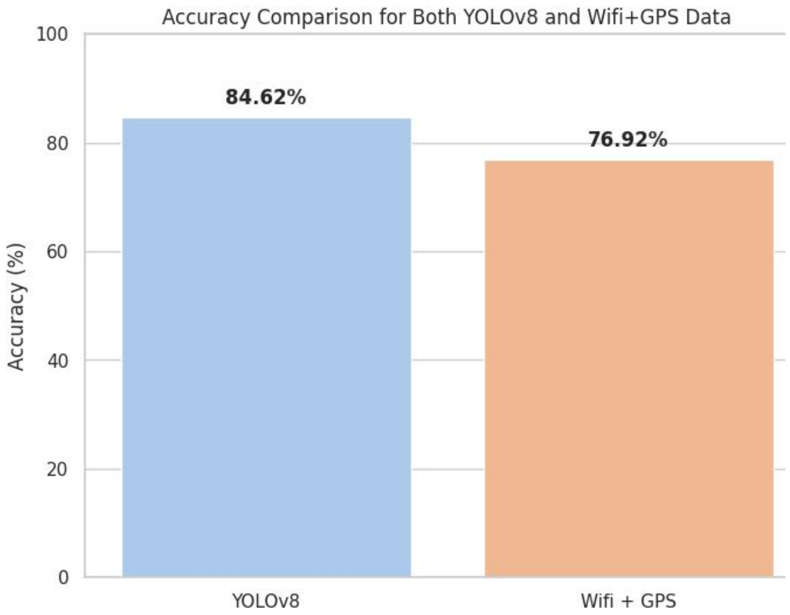
[fig5:GPS data]

Dataset

	Field	Dtype
	space	object
GPS :	latitude	float64
	longitude	float64
WiFi :	w01	int64
	w02	int64
	w03	int64
	w04	int64
Images :	folderPath	object

[fig6:Schema]

Results



[fig7:Comparison]

Results

	space	latitude	longitude	w01	w02	w03	w04	folderPath	objects	pred_spaces	pred_spaces2
0	gmtechLab	23.186912	72.627823	-60	-60	-60	0	/t01	mouse tv keyboard laptop cup remote dining tab...	gmtechLab	gmtechLab
1	cep105	23.188346	72.627877	0	-68	-70	-69	/t02	dining table chair bench	cep104	cep105
2	gmtechLab	23.186912	72.627824	-59	-69	-61	0	/t03	tv mouse keyboard laptop cup remote dining tab...	gmtechLab	gmtechLab
3	mtechLab	23.187083	72.628060	-62	-60	-62	0	/t04	tv mouse keyboard laptop suitcase bottle backp...	mtechLab	mtechLobby
4	roboticsLab	23.186913	72.627893	-38	-84	-37	0	/t05	tv mouse potted plant keyboard laptop person c...	roboticsLab	roboticsLab
5	roboticsLobby	23.186913	72.627894	-52	-52	-52	0	/t06	toilet bottle	roboticsLobby	roboticsLobby
6	mtechLobby	23.187142	72.628069	-61	-62	-61	0	/t07	tv train sink person bottle	mtechLobby	mtechLobby
7	vlsiLab	23.187076	72.628212	-72	-72	-72	0	/t08	tv mouse keyboard laptop chair refrigerator pe...	vlsiLab	vlsiLab
8	vlsiDesignLab	23.187269	72.628176	-72	-72	-72	0	/t09	tv mouse keyboard suitcase bottle chair backpa...	vlsiDesignLab	vlsiLab
9	cep202	23.188350	72.627873	0	-88	-89	-87	/t10	tv bottle dining table bench person chair	cep202	cep202
10	cep104	23.188513	72.627565	0	-69	-69	-66	/t11	dining table chair bench	cep104	cep104
11	cep105	23.188347	72.627878	0	-68	-69	-69	/t12	dining table chair bench	cep104	cep105
12	cep106	23.188350	72.627880	0	-68	-70	-71	/t13	refrigerator dining table chair	cep106	cep105

[fig8:Result Table]

Conclusion

➔ We extract the conclusion from this project that utilizing wifi and GPS data along with room images can produce results that are more precise.
➔ However, YOLOv8 frequently misdetects objects, and GPS signal is frequently unable to penetrate buildings.

Future Work

➔ Data Collection
➔ Handling Dynamic and Undefined Objects
➔ Extension to Whole Floor or Building Detection
➔ Semantic Object Relationships

References

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Thank You…!