Semantic Mapping using YOLOv8, WLAN, GPS

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***Abstract*—Indoor localization is an important component of modern infrastructure since it enables improved user experiences, security, and resource management within indoor environments. The project integrates YOLOv8 Object Detection, WiFi frequency analysis, and GPS signal processing to give a comprehensive method to indoor localization. The objective is to estimate interior locations correctly using visual content, WiFi signal intensities, and GPS data. A expanded dataset consisting of photos from several interior spaces is integrated with object lists, WiFi frequency measurements, and GPS signals in the implied technique. To identify things inside the room photos, YOLOv8, a cutting-edge real-time object identification framework, is used. Simultaneously, WiFi signal intensities from access points and GPS signals are combined to generate location fingerprints that demonstrate the unique characteristics of each indoor environment. A key innovation of this work lies in the combination of object detection results with WiFi and GPS data to determine the most probable location within the indoor space. The matching algorithm compares a test image's observed objects, WiFi signal intensities, and GPS signals to those in the learning set.**

***Index Terms*—YOLOv8, WiFi Frequency, GPS Signal, Logistic Regression**

I. Introduction

Indoor localization has emerged as a fundamental requirement for various applications spanning from smart building management to seamless indoor navigation. Unlike outdoor environments where GPS signals dominate, indoor spaces pose unique challenges due to signal attenuation, multipath effects, and the absence of clear line-of-sight to satellites. As a result, conventional GPS-based methods struggle to provide accurate indoor positioning. This project aims to bridge this gap by proposing an innovative approach that combines YOLOv8 object detection, WiFi bandwidth analysis, and GPS signal utilization to achieve accurate indoor localization.

The proliferation of Internet of Things (IoT) devices, along with rising demand for location-based services, has highlighted the importance of effective indoor localization solutions. Asset tracking, emergency response, and context-aware applications all require precise knowledge of a user's interior location. Existing systems frequently depend primarily on WiFi fingerprinting, Bluetooth beacons, or inertial sensors, which can be inaccurate and limiting in terms of scalability.

This initiative leverages the capabilities of multimodal data integration to address these difficulties. YOLOv8, which is recognized for its exceptional object identification skills, is combined with WiFi signal analysis and GPS data to deliver a comprehensive indoor localization solution. The technique attempts to improve accuracy and dependability while adjusting to the dynamic and complex nature of interior surroundings by integrating both optical and wireless data [2].

II. Background

In this section, We provide the background information for this project in detail. This Project focuses on the challenges of indoor localization, the significance of YOLOv8 object detection, WiFi frequency analysis, GPS signal utilization, and the benefits of multimodal data fusion. The challenges of signal attenuation and multipath effects in indoor environments are highlighted, which impact traditional GPS-based methods. YOLOv8's real-time object detection capabilities and WiFi frequency analysis's ability to capture spatial signal distributions are explained. While GPS signals are less reliable indoors, their potential for contributing to indoor context is acknowledged. The concept of multimodal data fusion, combining visual, wireless, and satellite-based data, is introduced as a means to enhance indoor localization accuracy. The background study sets the stage for the innovative approach proposed in the project, which integrates these technologies to overcome the challenges of accurate indoor positioning.

III. Technologies

A. **YOLOv8**

YOLOv8 was released in January 2023 by Ultralytics, the company that developed YOLOv5. YOLOv8 provided five scaled versions: YOLOv8n (nano), YOLOv8s (small), YOLOv8m (medium), YOLOv8l (large) and YOLOv8x (extra large). YOLOv8 supports multiple vision tasks such as object detection, segmentation, pose estimation, tracking, and classification [5]. YOLOv8 is the latest iteration in the YOLO family of detection models, which are known for their capabilities for joint detection and segmentation. Similar to YOLOv5, the architecture consists of a backbone, head, and neck. It boasts a new architecture, improved convolutional layers (backbone), and a more advanced detection head, making it a top choice for real-time object detection. YOLOv8 also offers support for the latest computer vision algorithms such as instance segmentation, enabling multiple object detection in an image or videos. The model uses the Darknet-53 backbone network, which is faster and more precise than the previous YOLOv7 [6] network. YOLOv8 predicts bounding boxes through an anchor-free. [1]

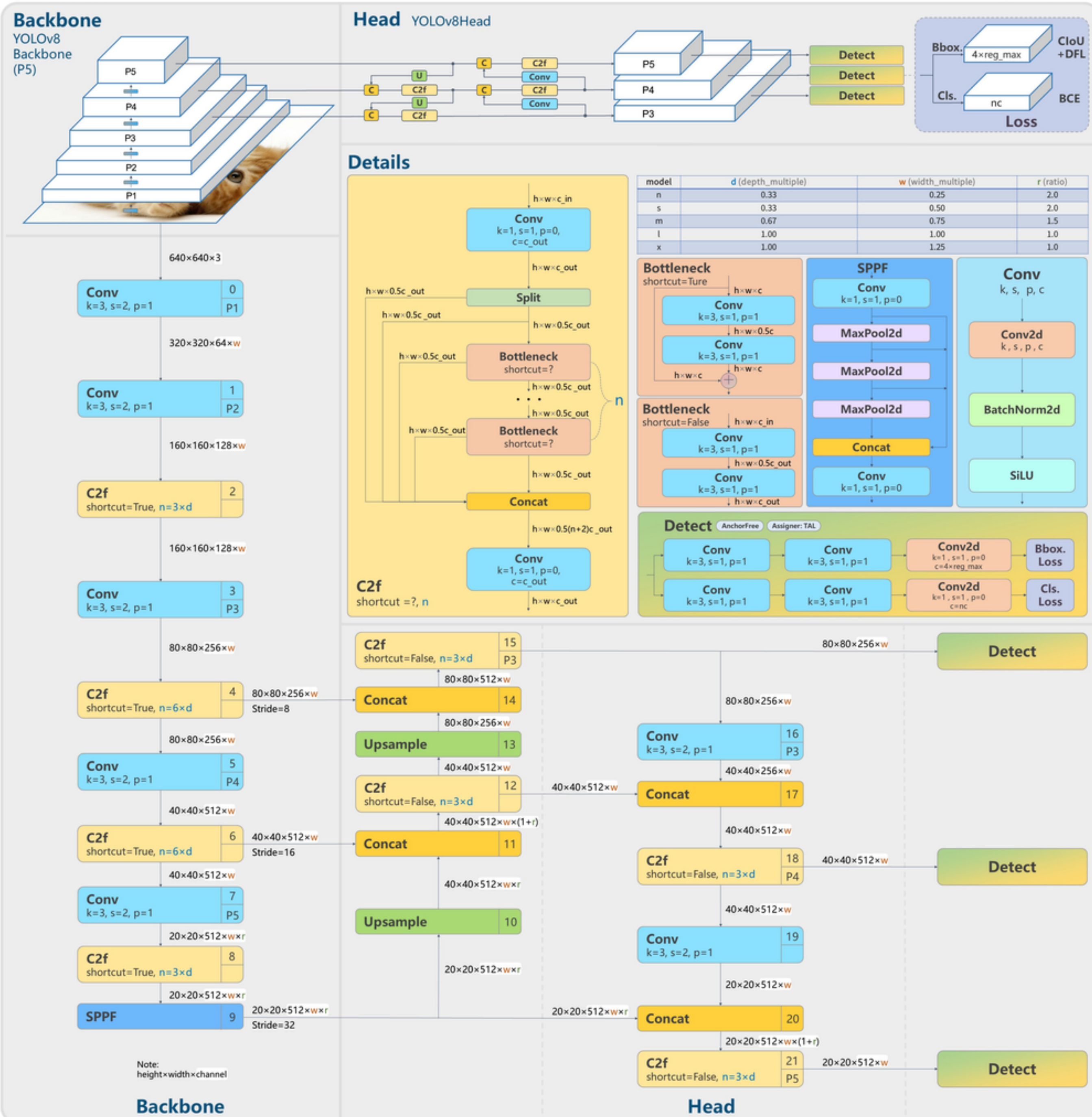

Fig. 1: YOLOv8 Architecture [5]

B. WiFi Frequency Analysis

WiFi frequency analysis involves the collection and analysis of WiFi signal strength measurements within indoor environments. WiFi networks emit radio waves at specific frequencies, and the strength of these signals can be measured in decibels relative to 1 milliwatt (dBm). By analyzing the distribution of WiFi signal strengths across an indoor space, it's possible to gain insights into the spatial characteristics of the environment, including signal attenuation, interference, and the presence of obstacles.

Understanding WiFi signal distribution is crucial for indoor localization projects. WiFi signals interact with walls, furniture, and other objects, leading to variations in signal strength across different locations. By mapping these variations, it's possible to create location fingerprints that help identify and differentiate between various indoor spaces based on their unique WiFi signal patterns.

WiFi frequency analysis provides a valuable layer of information that contributes to the overall indoor localization process. By combining WiFi signal strengths with other data sources like YOLOv8 object detection and GPS signals, the project aims to create a comprehensive understanding of indoor spaces. This integrated approach enhances the accuracy of indoor positioning and enables the determination of the best-matching room based on a combination of modalities.

C. GPS Signal Utilization

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. GPS signals are transmitted by a network of satellites orbiting the Earth and contain information about satellite positions and timestamps. Although GPS signals weaken and experience multipath effects indoors due to signal attenuation caused by walls and structures, they can still contribute to indoor localization in certain scenarios.
In indoor environments, where traditional GPS signals might be weak or entirely absent, utilizing available GPS signals or data derived from weak signals can provide additional contextual information. This context can be integrated with other localization methods, such as WiFi frequency analysis and object detection, to enhance the accuracy of indoor positioning.
Methods of Utilization:

1) **Coarse Location Estimation:** Weak GPS signals might still be received indoors, albeit with reduced accuracy. These signals can provide a rough estimate of the user's location within a building or floor.
2) **Contextual Information:** While weak GPS signals may not provide precise indoor positioning, they can offer additional context. For example, they can help validate or corroborate indoor location estimates derived from other sources.
3) **Hybrid Localization:** Hybrid localization methods combine data from multiple sources to enhance accuracy. GPS signals can be integrated with WiFi frequency analysis, object detection, and other techniques to create a more comprehensive localization solution. These hybrid methods aim to mitigate the limitations of individual techniques and leverage the strengths of each data source.

Challenges:

1) **Weak Signals:** Indoor environments typically receive weaker GPS signals due to signal blockage from structures. These signals might not be as accurate as outdoor signals.
2) **Multipath Effects:** Multipath interference occurs when GPS signals bounce off walls and structures, leading to signal distortions and inaccuracies. This effect can complicate the use of GPS data for indoor positioning.
3) **Coarse Accuracy:** The accuracy of GPS signals indoors is generally lower than in open outdoor spaces. However, even coarse location estimates can be valuable for certain applications.
4) **Integrity Monitoring:** GPS signal integrity monitoring is essential, as weak or inaccurate signals can lead to erroneous location estimates. Implementing measures to assess the quality of received signals is important.

D. Logistic Regression for Indoor Localization

Logistic Regression is a statistical technique primarily employed for binary classification tasks[4]. But, it can be extended to handle multi-class classification tasks through a technique known as ”One-vs-All” or ”One-vs-Rest.” This approach involves training multiple binary classifiers, each focused on distinguishing one class from the rest. In this project, We use this technique to predict the likelihood of each room's presence based on WiFi and GPS data.
Training Multiple Classifiers(One-vs-All): For each room in your dataset, train a separate Logistic Regression classifier. Each classifier learns to distinguish the signals and features specific to its assigned room from signals in all other rooms [3].
For each room, create a binary target variable 1 for the specific room and 0 for all other rooms combined and train separate Logistic Regression classifiers, each focusing on distinguishing a particular room.

Prediction for Multiple Classes: 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.

IV. Dataset

Creating a custom dataset for the project is an essential step in ensuring the effectiveness of indoor localization using YOLOv8 object detection, GPS signals, and WiFi strength analysis. The custom dataset is used to train, validate, and evaluate the indoor localization system. It combines visual, spatial, and wireless data to allow your project to reliably establish indoor locations based on WiFi strength, GPS signals, and YOLOv8 object detection results. **Dataset Components:**

1) **Images:** The dataset includes a collection of images representing different rooms within indoor environments. Each image captures the visual appearance of a specific room, including its layout, furniture, and any objects present. The diversity of room types and layouts ensures that your system can generalize well across different indoor spaces.
2) **GPS Signals:** For each room image, you've collected GPS signals that provide geographic coordinates (latitude, longitude, and possibly altitude). GPS signals can offer contextual information about the general location of each room within a building or complex. Even though GPS signals may be weaker indoors, they still contribute valuable data.
3) **WiFi Strength Measurements:** WiFi signal strength measurements have been recorded for each room. These measurements reflect the intensity of WiFi signals emitted by access points within or near the room. WiFi strength measurements are typically represented in decibels relative to 1 milliwatt (dBm), offering insights into the quality of WiFi connectivity within the room.

V. Working Steps

Here are the general steps that we followed to create this project:

TABLE I: Schema

Field	Dtype
space	object
latitude	float64
longitude	float64
w01	int64
w02	int64
w03	int64
w04	int64
folderPath	object

1) **Data Collection and Preprocessing:** We collected Images, Record GPS Signals Readings, and Measure the WiFi Signal Strengths of different Rooms. We annotated images with bounding boxes around objects of interest using the annotation tool Roboflow. Each bounding box should correspond to an object, and the annotation file should contain object labels and coordinates. After that, We divide our dataset into training, validation, and testing sets.
2) **Model Training:** We used the preprocessed dataset and annotations to train YOLOv8 using the training script provided by the framework. After that, We monitored training progress, analyze loss curves, and make adjustments to the learning rate and batch size as needed. We evaluate the trained model on the validation set and fine-tune the model parameters based on validation performance. Signal strength maps to each room using the recorded WiFi signal strength measurements and we use the recorded GPS signals to obtain coarse location estimates for each room.
3) **Testing:** We evaluate Localization Accuracy in this phase. In this, We assess the accuracy of your indoor localization system by comparing the predicted room labels with ground truth.

VI. Results

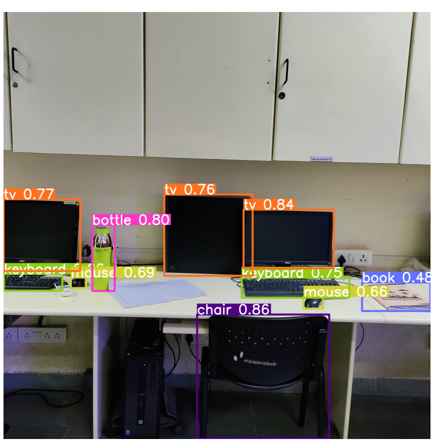

Fig. 2: Example of YOLOv8 Object Detection

YOLOv8 performs well at recognizing things inside photos of indoor spaces. The accuracy of 84.62% indicates the model recognizes objects correctly in the majority of circumstances. Identified objects help to improve spatial comprehension of the indoor environment.

The accuracy for indoor localization achieved by using Logistic Regression for WiFi and GPS signals is 76.92%. This level of accuracy indicates the system's ability to forecast the proper room based on WiFi signal strength and GPS context. The end result combines the results of YOLOv8

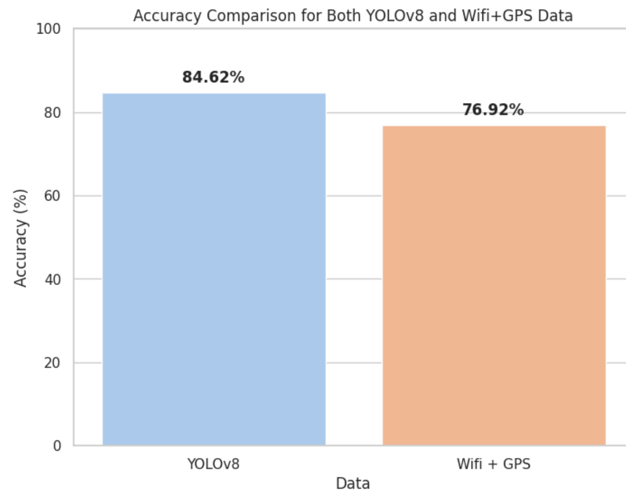

Fig. 3: Accuracy Comparison

Object Recognition with Logistic Regression-based WiFi and GPS localization. This comprehensive strategy depends on the benefits of both modalities, improving the overall accuracy of indoor localization [7].

VII. Conclusion

The Project effectively integrates YOLOv8's object identification capabilities with Logistic Regression-based WiFi and GPS localization to obtain overall accuracy that improves indoor placement. The findings provide a spotlight on the potential and constraints of multimodal indoor localization. YOLOv8's accuracy of 84.62% demonstrates its effectiveness in recognizing things within indoor room pictures. Accurate object identification improves spatial comprehension and contributes to indoor localization precision. The combined accuracy of 76.92% achieved through WiFi and GPS localization using Logistic Regression highlights their importance in indoor locations. Despite WiFi signal loss and the limitations of indoor GPS signals, these Logistic Regression approaches give useful information.

VIII. Future Scope

The project has a lot of potential for future development. Here are some possible areas for improvement:

1) **Refining Model and Semantic Understanding**
   - **Fine-Tuning Object Detection:** We have investigated techniques to improve object detection accuracy, especially for objects currently being misidentified, and fine-tune the YOLOv8 model on misclassified objects and update bounding box annotations.
   - **Semantic Object Relationships:** We need to explore methods to establish semantic connections between detected objects and develop algorithms

to infer relationships, positions, or interactions between objects for a richer spatial understanding.

2) **WiFi Frequency Analysis and Contextual Insights** We need to analyze these frequencies to gain insights into areas with higher or lower WiFi activity. We have to develop techniques to create contextual WiFi signatures for rooms, combine signal strength with frequency count, and use these signatures to enhance the accuracy of WiFi-based localization.
3) **Handling Dynamic and Undefined Objects** We will investigate dynamic object tracking methods to account for objects that change position or appearance. This could involve employing techniques like object-tracking algorithms and consider ways to track and localize these objects while maintaining overall accuracy.
4) **Extension to Whole Floor or Building Detection** Extend the localization system to encompass multiple rooms, floors, or even an entire building. We will train models to recognize higher-level spatial contexts, such as floors and buildings and utilize existing localization methods to contribute to the hierarchical model's accuracy.

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