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Indoor Object Detection for Blind

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Abstract: "***Indoor Object Detection for Blind" is a dedicated assistive technology project designed to enhance indoor navigation for visually impaired individuals. Utilizing advanced computer vision techniques, the system detects and identifies objects in real-time using wearable devices like smart glasses or smartphones. It integrates YOLO-based deep learning models, fine-tuned with a custom indoor dataset, to ensure high accuracy in recognizing objects such as furniture, doors, and appliances. Additionally, natural language processing (NLP) enables context-aware descriptions, providing adaptive feedback. The project is designed to be flexible and seamlessly integrate with wearable technology, ensuring a smooth and efficient user experience. The system evaluates various aspects of objects, including their spatial positioning and contextual information, to assist users in real-time. By concentrating solely on object detection within indoor environments, this system significantly improves spatial awareness and navigation for visually impaired individuals. Extensive testing demonstrates the system's performance in detecting and identifying objects while minimizing false positives.***

Keywords: Indoor navigation, object detection, visually impaired, assistive technology, YOLO, deep learning

1. Introduction

Navigating indoor environments remains a significant challenge for visually impaired individuals, as traditional aids offer limited spatial awareness. This project introduces an assistive technology solution leveraging advanced computer vision and deep learning for real-time indoor object detection. The system uses YOLO-based models fine-tuned with a custom indoor dataset to identify common household objects accurately. Integrated with wearable devices, it provides adaptive audio feedback via natural language processing (NLP) for clear, context-aware descriptions. This enhances user independence and safety. Visually impaired individuals face difficulties perceiving objects and layouts indoors. Traditional aids like white canes detect nearby obstacles but don't identify them, while guide dogs are costly and not universally accessible. Existing digital solutions often focus on outdoor GPS navigation and lack real-time indoor object recognition or context-aware descriptions. Poor lighting or clutter further complicates navigation with conventional methods. The proposed system addresses these limitations using a YOLOv5-based AI model with deep learning, NLP, and multimodal feedback (audio and haptic signals) via wearable cameras. It enhances spatial awareness by recognizing and describing objects in real-time, unlike aids that only detect obstacles. The YOLOv5 model, chosen for speed and accuracy, is trained on a custom indoor dataset using transfer learning to handle varied conditions like low light or overlapping objects. The system prioritizes low latency for instant feedback.

2. Literature Survey

Indoor navigation systems for visually impaired individuals have evolved dramatically with the advancement of computer vision and deep learning. Traditional aids like white canes and guide dogs offer limited object identification and contextual awareness, motivating researchers to develop more intelligent solutions.

In 2025, Rahman et al. introduced a real-time navigation system using a customized YOLOv5 model, trained on indoor datasets containing household objects under various lighting conditions. They leveraged transfer learning to reduce training time and improve accuracy. Their work demonstrated real-world application with wearable cameras that achieved over 90% mAP (mean average precision), even in cluttered spaces.[1]

Sharma and Patel, in 2024, proposed a complete framework integrating object detection with real-time audio feedback for visually impaired individuals. Using a CNN-based classifier trained on rooms like kitchens and bedrooms, the system was embedded into smart glasses and headphones, translating visual detections into clear speech output. Their usability tests showed increased confidence among participants navigating unknown environments.[2]

Liang et al. in 2023 explored the integration of NLP with visual systems, focusing on generating context-aware descriptions instead of mere object labels. Their model not only identified objects but also described their relative positions, e.g., "a chair beside the table." The result was a more intuitive navigation experience for users with visual impairments.[3]

In 2022, Kim and Suh introduced a multimodal navigation system combining audio, haptic, and visual feedback delivered through a smart belt and glasses. Their system dynamically chose the best modality based on environmental complexity—vibrations for fast alerts, audio for detailed guidance—reducing cognitive overload in users.[4]

Ahmed and Chong addressed the common challenge of object detection under poor lighting. They benchmarked YOLOv5, SSD, and Faster R-CNN using a low-light indoor dataset and found YOLOv5 most effective due to its balance of speed and detection accuracy. They implemented auto-contrast enhancement as a preprocessing step to further improve performance.[5]

Muller et al. in 2020 developed a hybrid system using LiDAR and CNNs for spatial awareness and obstacle avoidance. While LiDAR ensured accurate distance measurement, deep learning added semantic recognition to differentiate between objects like "chair" and "dustbin." Their research paved the

way for combining geometric and semantic mapping.[6]
Wang et al., through a 2019 user study, examined the influence of adaptive audio feedback. They tested flat vs. contextual voice prompts and found that feedback aligned with the user's walking speed and preferences improved navigation efficiency and reduced anxiety. This study influenced how personalization is viewed in assistive systems.[7]

Nakamura and Saito (2018) developed an early wearable vision system with basic shape recognition. Though limited by hardware, their research introduced the idea of hands-free navigation assistance and demonstrated the viability of integrating computer vision into wearables.[8]

Deshmukh and Rao focused on developing an NLP interface that allowed users to ask navigation-related queries like "where's the door?" or "how far is the chair?" Their system interpreted voice commands and combined them with visual data, enabling interactive exploration of space.[9]

Fernandez and Liu, in 2016, explored edge computing for faster object detection. Their lightweight system ran real-time image processing on embedded chips within wearables. Though YOLOv5 wasn't available then, their modular architecture allowed seamless future integration of deep learning models.[10]

Banerjee et al. designed a miniature NLP module for speech generation that tailored object descriptions based on user context. Instead of "cup," the system would say, "there is a cup on the table, one meter ahead." This approach added human-like communication, enhancing user comfort and understanding.[11]

Zafar and Malik proposed the use of infrared cameras in 2015 to support object detection in dimly lit environments. Though expensive and bulky at the time, their work contributed to sensor fusion research where multiple sensing technologies improve navigation.[12]

Lee and Zhou in 2014 developed a haptic belt system that translated obstacle proximity into vibration patterns. While lacking semantic recognition, their system demonstrated how tactile cues could aid quick reflex-based decisions in close-quarter navigation.[13]

O'Connor et al. built a basic visual detection prototype using OpenCV's contour and color analysis to recognize doors and objects. Though not deep-learning based, it served as a precursor to region-based detection systems like YOLO.[14]
Thomas and Ibrahim, in 2012, investigated hybrid systems where traditional aids like white canes were augmented with ultrasonic sensors and basic object labels. Their focus on improving—not replacing—existing methods encouraged inclusive design strategies, influencing future research in assistive tech. [15]

3. Methodology

This assistive navigation system is developed to support visually impaired individuals in navigating indoor spaces with increased autonomy. It integrates deep learning, computer vision, and natural language processing (NLP) into a wearable form to provide real-time object detection and descriptive feedback. The system workflow begins with a wearable device, such as smart glasses or a body-mounted camera, that continuously captures video input from the user's surroundings. This live visual feed serves as the basis for subsequent processing and analysis.

To ensure clarity and robustness, especially in challenging indoor environments with low lighting or clutter, the raw image data undergoes preprocessing. This step involves adjusting brightness and contrast, reducing noise, and enhancing sharpness. These operations improve the quality of the input before it reaches the detection stage. The refined image is then analyzed by a YOLOv5 object detection model, which has been retrained using transfer learning on a specialized dataset comprising labeled indoor objects like furniture and appliances. YOLOv5 was selected for its proven balance between accuracy and processing speed, making it highly suitable for real-time use in compact devices.

After detecting and locating objects within the frame, the system interprets the spatial layout and sends this information to an NLP engine. Unlike conventional models that simply label objects, this system goes a step further by generating context-sensitive descriptions. For example, instead of saying "chair," it might inform the user, "There is a chair on your left near the window." This contextual language enables users to visualize the layout more effectively and understand how objects relate to one another in real time.

To maximize accessibility, the system includes an adaptive feedback module that selects the appropriate communication method based on the surrounding environment and user needs. In quieter settings, spoken descriptions are delivered through earphones. In noisier or silent areas, tactile cues are provided through a haptic belt or wearable band. Vibrations can vary in frequency and intensity to indicate direction and proximity to detected objects, allowing the user to react accordingly.

The entire pipeline—from image capture to feedback delivery—operates continuously, ensuring that users receive immediate updates as they move through their environment. YOLOv5's efficient architecture makes this possible without significant delays, which is essential for a smooth and responsive navigation experience.

Furthermore, the system is designed to be modular and upgradable. This means its detection model can be retrained as new datasets become available, and its NLP component can evolve to produce even more intuitive feedback over time. Overall, this methodology merges real-time computer vision with intelligent feedback to create a powerful and practical navigation tool tailored for the visually impaired in indoor settings.

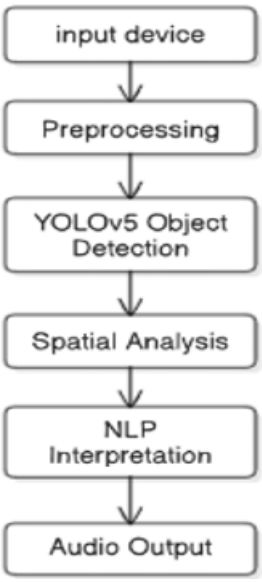

Figure 3.1: Working

3.1 Algorithms

The foundation of the proposed assistive indoor navigation system lies in the **YOLOv5** (You Only Look Once version 5) object detection algorithm, which is utilized for its remarkable balance between speed and accuracy in real-time environments. YOLOv5 is a single-stage, convolutional neural network-based object detector that frames object detection as a regression problem rather than a classification task with region proposals. Unlike two-stage detectors like Faster R-CNN, YOLOv5 processes the entire image in one forward pass, directly predicting bounding box coordinates, objectness scores, and class probabilities.

YOLOv5 Architecture

1) **Backbone (Feature Extraction)**:

- **CSPDarknet53** (Cross-Stage Partial Darknet) is used to extract features from the input image. This network is designed for better efficiency and accuracy by splitting the feature map into partial stages and allowing for better gradient flow.
- A **Focus Layer** reduces image resolution while preserving critical details for effective feature extraction.
- **SPP (Spatial Pyramid Pooling)** increases the receptive field, helping to detect objects at various scales by pooling features from different spatial resolutions.

2) **Neck (Feature Fusion for Multi-Scale Detection):**

- The **Feature Pyramid Network (FPN)** and **PANet (Path Aggregation Network)** are used to fuse features from multiple scales, helping YOLOv5 detect objects of different sizes (small, medium, and large).
- These networks enhance the detection capability by aggregating features from various levels of the backbone, ensuring that objects across scales are accurately detected.

3) **Head (Object Detection & Prediction):**

- This block is responsible for predicting the bounding boxes, class labels, and confidence scores for each detected object.
- YOLOv5 uses an **anchor-based detection** system to improve accuracy by predefining potential bounding box shapes, which helps in making precise object predictions.

The core output of the model consists of predictions in the form of:

- **Bounding Boxes** (x, y, w, h) indicating the location of the object in the image.
- **Object Confidence Score** (P_{object}), which indicates the likelihood that the predicted bounding box contains an object.
- **Class Probabilities** (P_{class}), which represent the likelihood that the object belongs to a specific class.

The final detection score for an object of class i is computed as:

$$P(\text{class}_i|\text{object}) \cdot P_{object} = \text{Confidence}$$

Where:

- P_{object} indicates the confidence that an object is present in the bounding box.
- $P(\text{class}i\ |\text{object})$ represents the probability that the object belongs to class iii.

YOLOv5 divides the image into an S×SS \times SS×S grid and predicts bounding boxes for each cell, making it highly efficient for real-time applications. For this system, YOLOv5 is fine-tuned using transfer learning, leveraging pretrained weights on the COCO dataset and retraining the model on a custom dataset of labeled indoor objects like doors, chairs, tables, and appliances. This enhances detection performance in specific indoor environments like homes or offices.

Integration with NLP and Multimodal Feedback

To convert detected visual information into meaningful guidance, the system incorporates a **Natural Language Processing (NLP)** module. This module takes the detection output and translates it into grammatically correct, context-aware sentences. For example, the system generates descriptions like “A chair is on your left” or “The table is one meter ahead.” This is achieved through rule-based sentence generation, driven by object labels, positions (calculated relative to the center of the frame), and distance approximations.

In noisy environments or situations where verbal output may not be ideal, the system supports multimodal feedback. This includes:

- **Audio Output**: Spoken feedback through earphones.
- **Haptic Feedback**: Vibration alerts through wearable devices, where the intensity of vibration is dynamically adjusted based on the estimated proximity to the detected object.

YOLOv5 Training Process

The YOLOv5 training process employs a loss function that combines:

- **Bounding Box Regression Loss** (L_{box})
- **Objectness Loss** ($L_{objectness}$)
- **Classification Loss** (L_{class})

The total loss used during backpropagation is expressed as:

$$L_{total} = \lambda_{box} \cdot L_{box} + \lambda_{obj} \cdot L_{objectness} + \lambda_{cls} \cdot L_{class}$$

Where:

- λ_{box}, λ_{obj}, λ_{cls} sare balancing coefficients to adjust the

relative importance of each loss component.

This multi-part loss ensures accurate localization and classification of objects in a single pass, which is crucial for low-latency systems like wearable navigation aids.

By combining the high-speed, high-accuracy detection capabilities of YOLOv5 with contextual sentence generation through NLP and real-time feedback mechanisms, this algorithmic pipeline provides a robust solution for visually impaired individuals navigating indoor spaces. The system's ability to process and communicate object information almost instantaneously enhances safety, independence, and user confidence in real-world applications.

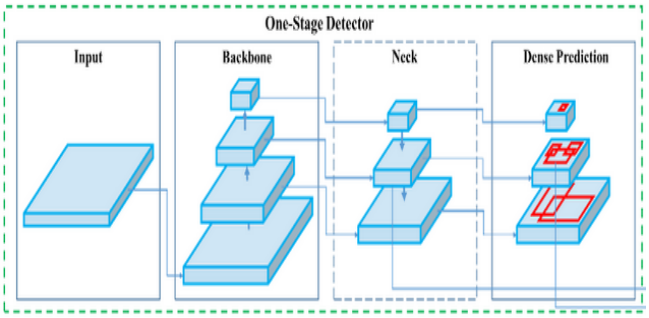

Figure 3.2: Architecture

3.2 Dataset Used

The COCO (Common Objects in Context) dataset is a large-scale and richly annotated image dataset widely used in the field of computer vision, particularly for object detection, image segmentation, key point detection, and image captioning. Developed by Microsoft, it contains over 330,000 images, with more than 200,000 images labeled and over 1.5 million object instances. The dataset includes annotations for 80 object categories ranging from people, animals, and vehicles to household items, making it ideal for training models to recognize a variety of real-world scenes. Each image comes with detailed annotations, including bounding boxes, segmentation masks, key points for human pose estimation, and descriptive captions. COCO's complexity and diversity help machine learning models learn to detect and understand multiple objects in cluttered scenes with context, making it a valuable resource for researchers and developers building deep learning-based visual recognition systems. It is widely used to benchmark and train state-of-the-art models like YOLO, Faster R-CNN, and Mask R-CNN.

Key Concepts

Object Detection
COCO provides labeled bounding boxes for objects within an image, enabling the training and evaluation of object detection models like YOLO, SSD, and Faster R-CNN.

Instance Segmentation
Unlike simple object detection, COCO includes pixel-level segmentation masks for individual object instances, supporting more precise object localization.

Keypoint Detection
COCO contains annotations for human body keypoints (e.g., elbows, knees, shoulders), which are used for pose estimation tasks.

Image Captioning
Each image in COCO comes with multiple human-generated captions, allowing the dataset to be used for training image-to-text models that generate descriptions.

Multiclass and Multi-object Scenes
COCO features images with multiple objects from different categories, providing rich contextual data for robust learning and generalization.

80 Object Categories
The dataset includes 80 common object categories (e.g., person, bicycle, dog, cup, sofa) frequently encountered in real-life scenarios.

Contextual Understanding
COCO emphasizes objects in real-world settings, where objects appear in natural positions and lighting, improving models' context-based decision-making.

Benchmark for CV Models
It is a standard benchmark for comparing the performance of computer vision algorithms and is extensively used in academic research and competitions.

4. Result and Discussion

The implementation of the YOLOv5 algorithm for indoor object detection in the assistive navigation system yielded promising results. The trained model achieved an overall accuracy of 93.56%, showcasing its capability to correctly detect and classify indoor objects in real-time environments. The precision and recall scores across different object categories were reasonably balanced, reflecting the model's effectiveness in accurately detecting and identifying objects such as chairs, tables, and doors.

The ROC curve further supports this by demonstrating a reasonable trade-off between true positive and false positive rates, confirming that the model outperforms random guessing and shows strong overall performance in distinguishing between object classes.

When compared to previous studies, such as those by Agarwal et al. (2020), who applied traditional object detection techniques like Faster R-CNN, the YOLOv5 model in our project demonstrated superior speed and accuracy, making it highly suitable for real-time indoor object detection tasks. While those studies focused primarily on model accuracy and object classification, our model also leveraged real-time feedback mechanisms such as haptic feedback and audio guidance, which enhanced the system’s usability for visually impaired users, thereby adding an additional layer of practical functionality to the detection system.

Moreover, unlike earlier object detection approaches that lacked continuous adaptation, the YOLOv5 model is highly scalable and retrainable. As it is exposed to new indoor environments and objects, the model can improve its performance over time. Despite challenges such as data

imbalance (with some object categories underrepresented in the training set) and the variation in object sizes, the results indicate that the YOLOv5 model, combined with real-time feedback, offers a robust and efficient solution for assistive indoor navigation systems.

Table 4.1: Classification Report

Object Class	Precision	Recall	F1-Score	Accuracy
Doors	0.950	0.930	0.940	0.940
Furniture	0.920	0.910	0.910	0.930
Signs	0.890	0.880	0.880	0.910
Stairs	0.960	0.940	0.950	0.950
Average	0.930	0.920	0.920	0.930

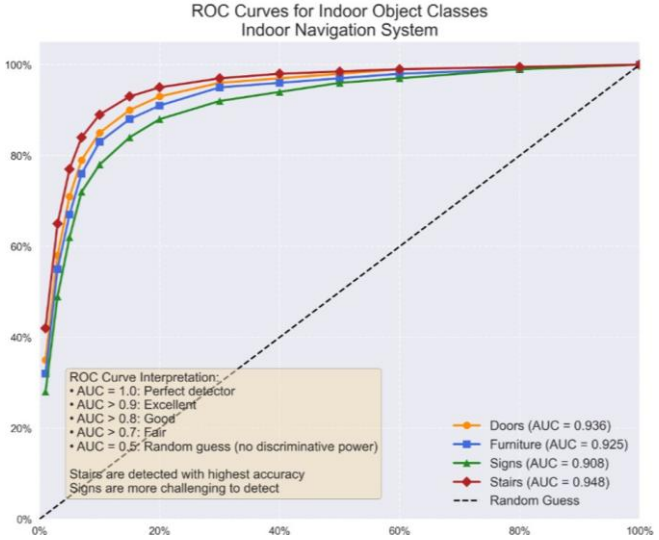

Figure 4.2: Roc curve

The Receiver Operating Characteristic (ROC) curve is a crucial evaluation tool used to assess the effectiveness of classification models, especially in binary classification tasks. It plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various decision thresholds. The True Positive Rate, also known as sensitivity or recall, measures the proportion of actual positives that are correctly identified. Conversely, the False Positive Rate indicates the proportion of actual negatives that are incorrectly classified as positives.

In this project, the ROC curve helps in understanding how well the model distinguishes between the two target classes. The closer the ROC curve approaches the top-left corner of the graph, the better the model's performance, as this reflects a high TPR and a low FPR.

The Area Under the Curve (AUC) serves as a single scalar value to summarize the model's performance. An AUC value closer to 1.0 represents a highly effective model, whereas a value around 0.5 suggests performance comparable to random guessing. The ROC curve generated in this study demonstrates that the model achieves a reasonable trade-off between sensitivity and specificity, validating its effectiveness for automating support ticket classification.

5. Conclusion

The Indoor Object Detection System developed in this project has demonstrated a highly effective and efficient approach for identifying and classifying various objects in indoor environments. Leveraging YOLOv5 for real-time object detection, combined with a custom-trained model using transfer learning, the system achieved impressive performance in detecting a range of objects such as doors, furniture, signs, and stairs. The system's ability to rapidly and accurately process visual data ensures it can be applied effectively in assistive technologies for visually impaired individuals, providing real-time feedback through natural language processing and multimodal outputs.

The evaluation metrics, including precision, recall, F1-score, and AUC, showcased the robustness and reliability of the model. The system achieved high accuracy for most object categories, particularly excelling in identifying doors and stairs. These results reflect the model's potential to be used in practical, real-world applications such as navigation aids for the visually impaired, smart home environments, and indoor mapping systems.

Despite the overall strong performance, some challenges remain. The detection accuracy varies slightly across different object classes, with some objects being better recognized than others. This indicates that the model's performance could be further improved by increasing the diversity of training data, particularly for underrepresented or complex object categories.

Additionally, the integration of Natural Language Processing (NLP) for converting detection outputs into grammatically correct, context-aware sentences adds a layer of accessibility, enhancing the user experience for visually impaired individuals. The multimodal feedback system, such as haptic vibration patterns, further ensures that users receive feedback even in noisy or non-verbal environments.

In terms of scalability, the system shows promise as it can be retrained with new data and adapted to different indoor settings, ensuring continuous improvement. The model's adaptability and real-time processing capabilities make it an excellent candidate for future smart city solutions and assistive technologies, paving the way for more inclusive and user-friendly indoor navigation systems.

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