



SafeWalk

for the Visually Impaired

Empower visually impaired individuals with the safety, independence, and confidence to navigate the world.



Our Team: Innovators in Accessibility



Kris Junghee Lee

Data Collection, Yolo Fine tuning, Alert Rule Setting ,
App Test & Development



Helen Hu

Datasets Collection &
Cleaning, Model Evaluation



Ke Zhang

Data pipeline, VLM, App
Test and Webmaster



Ula Zhu

Project Manager, UI/UX
design

Problem Statement

- **Over 36 million** people globally live with severe visual impairments, which is expected double in the next 30 years
- **More than 270,000** pedestrians are killed on roads each year

Road deaths



TRANSPORTATION

Disabled People Are Dying in America's Crosswalks. We Need to Protect Them.

The data on traffic fatalities and injuries doesn't account for their needs or even count them. Better data would enable better solutions.

OPINION | March 27, 2024 • Claudio Folke



Diego Serrano/istock.com

Latest News

FINANCE
Under Trump, Medicaid Faces a 'Reset Moment'
Jan. 12, 2025

WORKFORCE
Minimum Wages Are Rising in Nearly Half the States This Year
Jan. 11, 2025

POLITICS
Jimmy Carter's Redemptive Record on Race and Injustice
OPINION | Jan. 13, 2025

ARTIFICIAL INTELLIGENCE
Health-Care AI Requires a Lot of Expensive Humans
Jan. 12, 2025

NEWS IN NUMBERS
10
January 19, 2025

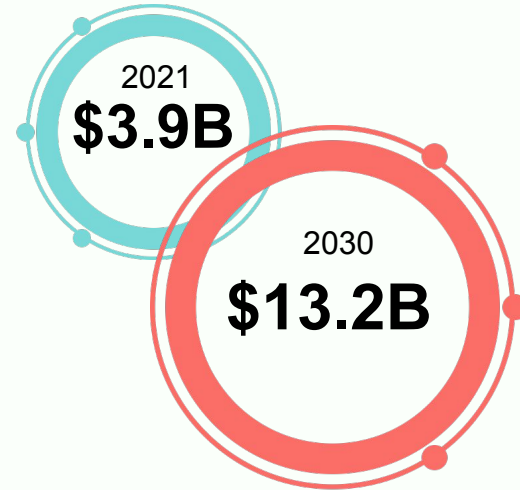


Target Users

Visually impaired individuals living in urban areas with smartphone accessibility



Market Size



Interview with Domain Expert



Carrie on Accessibility

@carrieonaccessibility · 7.53K subscribers · 429 videos

Hi! Welcome to Carrie on Accessibility—CoA for short! ...more

discord.gg/sQrH377mkh and 6 more links

Subscribe

Join

Home

Videos

Shorts

Live

Podcasts

Playlists

Posts



SafeWalk Key Features



Obstacle Detection

Identify outdoor obstacles
Landscape mode



Adaptive Warning

"Be careful" for close objects
"In the front" for further objects
Direction: front, left, right



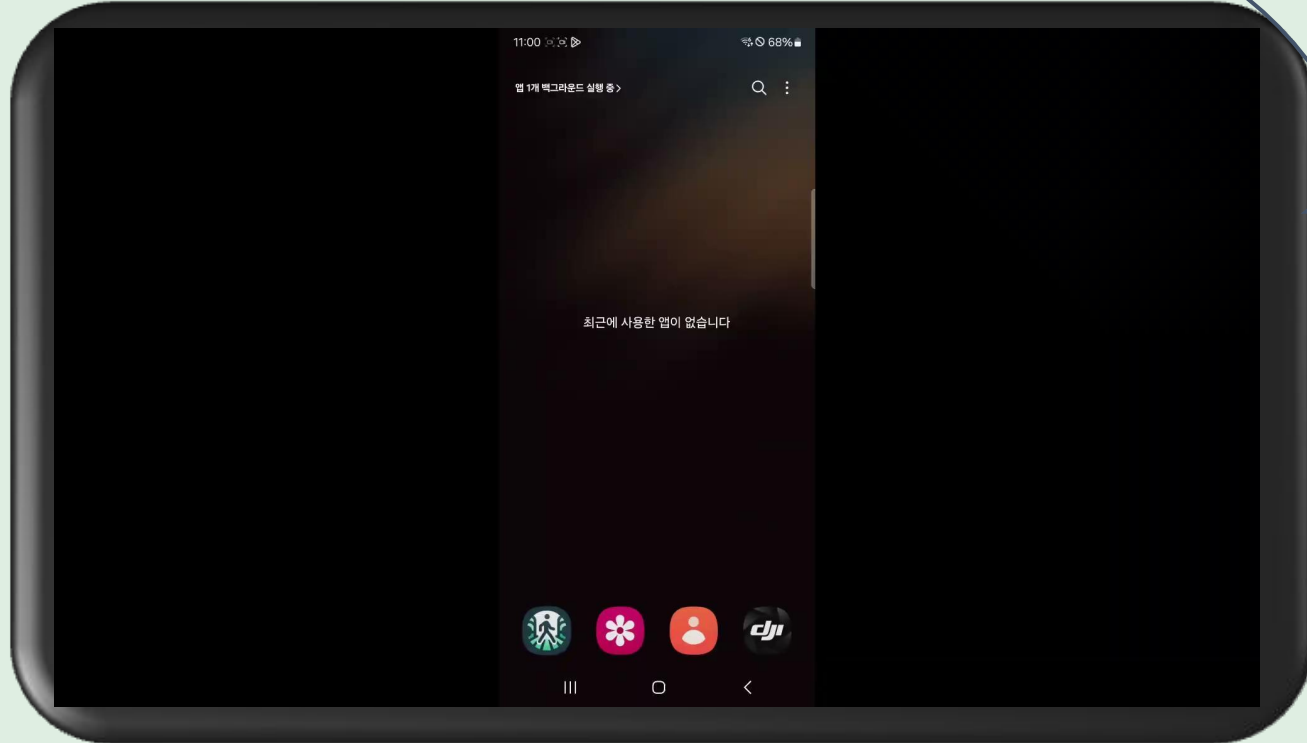
Surrounding Description

Helps users understand what's in front of them real-time.



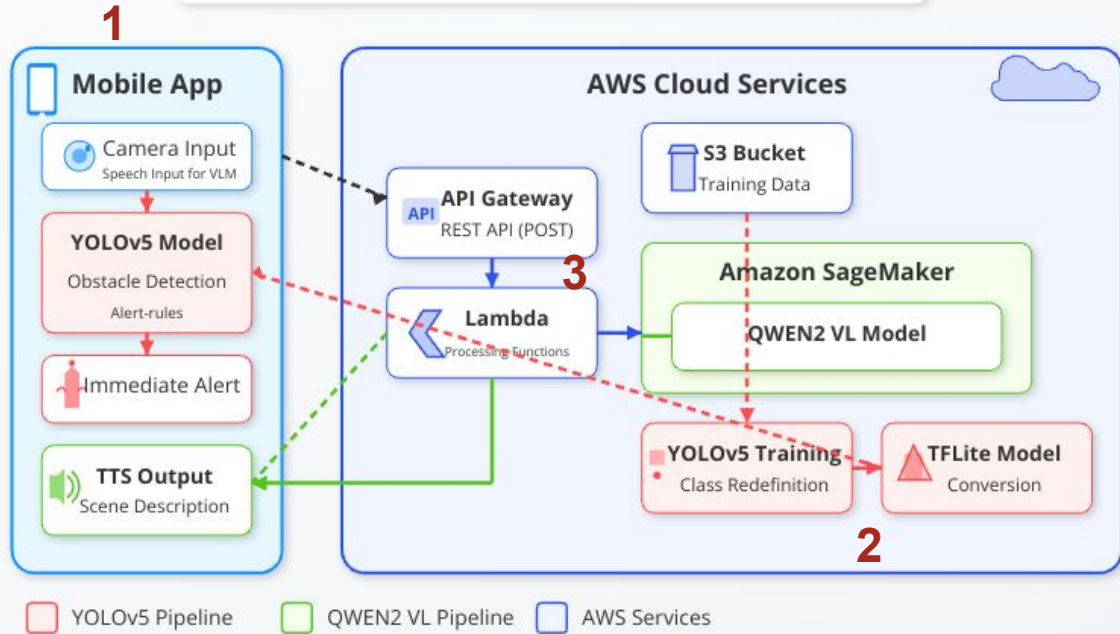
Voice Assistant

Answer questions



System Architecture Design

SafeWalk: System Architecture



Mobile App Front-End

- Real-time Obstacle Detection & Alerts
- Scene Description via VTT and TTS Output
- Flutter was used to make front-end

YOLOv5 Pipeline

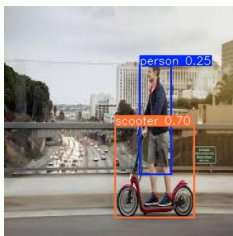
- Fine-tuned on Custom Dataset
- Converted to TFLite for Mobile

Qwen2-VL Pipeline

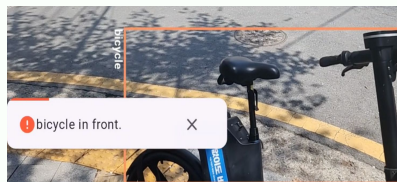
- Custom Prompt Engineering for Accessibility
- Lambda + API Gateway for Mobile Integration

Overcoming Technical Challenges

“scooter”



“Be Careful Bicycle in front”



“The image shows a city street scene during the day ...”



1

Identify Obstacles

- Train dataset
- Model selection
- Accuracy

2

Alert Rules

- Usability
- Informative warning

3

Scene Description

- VLM Model Evaluation

Build Unique Datasets with Real-World Examples



Data Classes

▶ Common (14 classes)

Person, Bicycle, Car, Motorcycle, Bus, Truck, Traffic Light, Fire Hydrant, Stop Sign, Parking Meter, Bench, Bird, Cat, Dog

▶ Additional (13 classes)

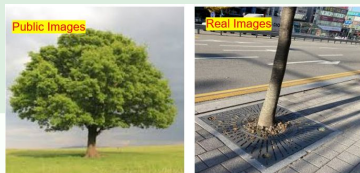
Pole, Pothole, Tree, Scooter, Bollard, Traffic Cone, Bad Roads, Fence Barrier, Stairs, Trash Bin, Downstairs, Upstairs, Crosswalk

Challenges

Required many dataset due to Catastrophic Forgetting of Pre-trained model

Missing labels from Public images

Different images between Public Vs. Real-World

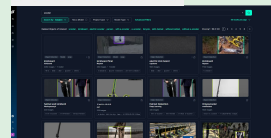


Solution

COCO dataset

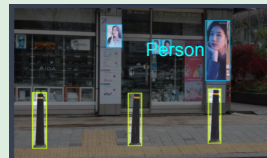


roboflow



kaggle

Auto Label Function

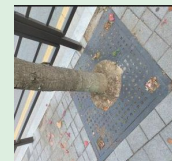


Wrong-Auto Labeler Example

Human Final check



- Self-taken & labeled real-world images
- Data augmentation



Augmentation

Final Dataset: 90,855

Selecting the Base Model to Reach Our Goal



Performance-Oriented Model Comparison

	Precision	Recall	mAP 0.5	mAP 0.5-0.9
Yolo v5s	0.65	0.48	0.52	0.31
Yolo v7s	0.63	0.33	0.37	0.20
Yolo v11s	0.66	0.53	0.56	0.37

- mAP 0.5: Mean Average Precision calculated using a single Intersection over Union (IoU) threshold of 0.5.
- mAP 0.5-0.9: Mean Average Precision averaged over multiple IoU thresholds, ranging from 0.5 to 0.95 in increments of 0.05.

Deployment-Focused Comparison

Well-established as a **lightweight version**, **Robust compatibility** with various deployment

Higher accuracy but **slower inference**
Need **Additional Effort** for compatibility

While Performance metrics show only minor differences, Yolo v5s shows substantial competitiveness in deployment



Final Model Approach
Yolo v5s + Fine tuning

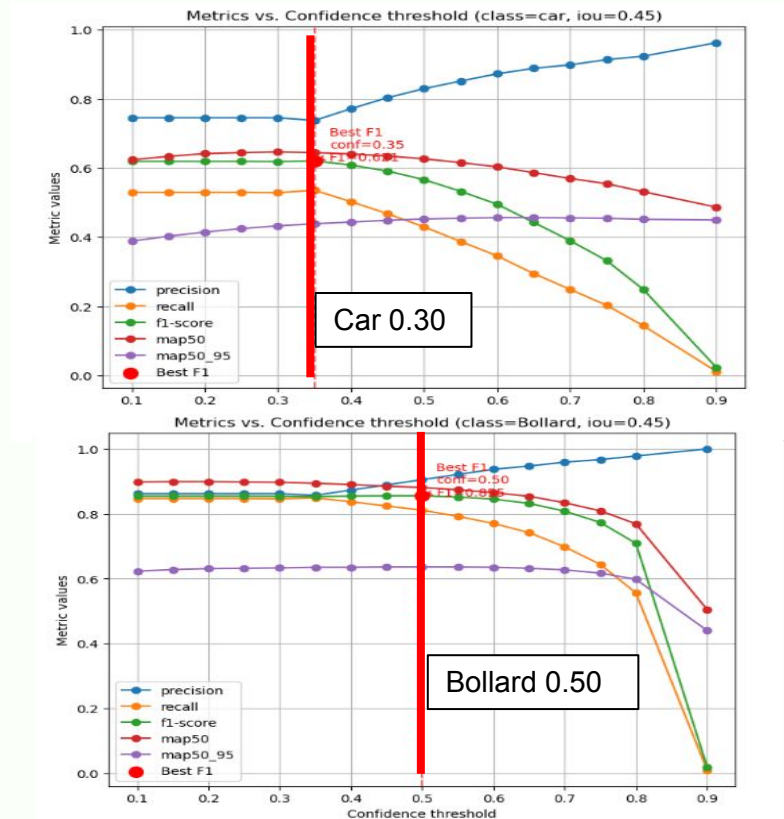
Optimizing performance with Fine-tuning

Fine Tuning Approach

- Change optimizer (SGD -> Adam)
- Adjusted Learning Rate (0.01 -> 0.001)
- Increased Epochs (100)
- Class Weight Parameter
- Under sampling
- Oversampling by data augmentation
- **Apply relative Threshold by class**

- SGD: Stochastic Gradient Descent
- Adam: a method for stochastic optimization

Example of threshold adjustment



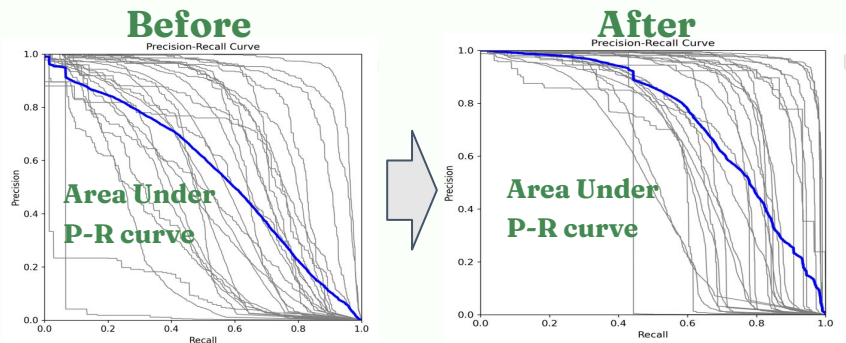
Optimizing performance with Fine-tuning



Final Evaluation

	Precision	Recall	F1 Score	mAP	mAP
Basemodel	0.65	0.48	0.54	0.52	0.31
Fine-Tuned model	0.82	0.67	0.73	0.76	0.54

Precision Recall Curve



iOU Threshold:0.5

Object Detection Example

Before



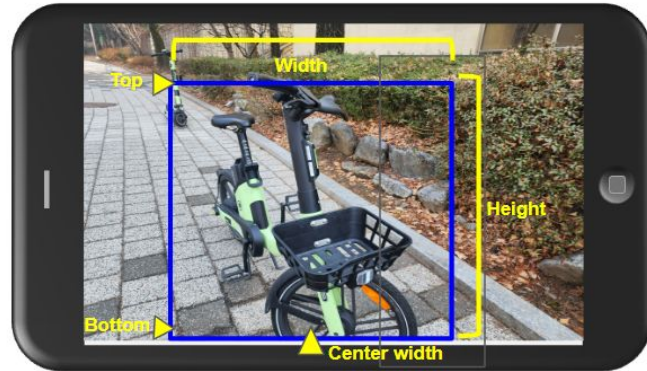
After



Building Adaptive Alert for better usability



Rule Development using Bounding Box Parameter



“Be Careful Bicycle in front”

Key Objective

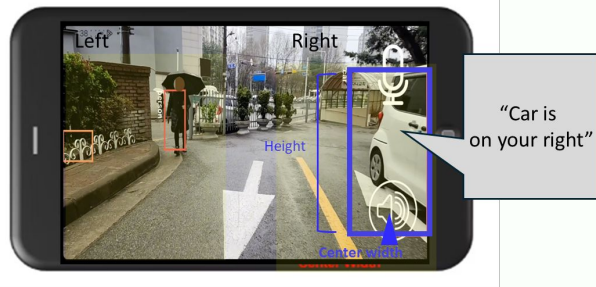
- Only alerts when it matters to *reduce fatigue*
- Directional guidance for *enhanced usability*
- Right-time warnings for *safer decisions*

Building Guided Alert for better usability

Adaptive Alert

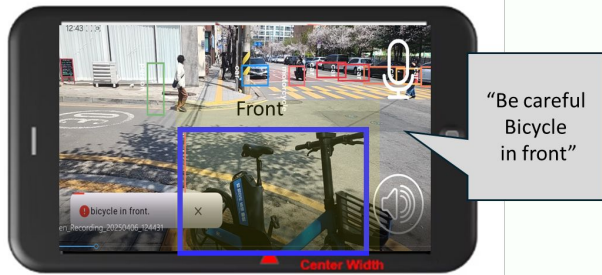
Detect Mode (Directional Guide)

- Parameter : Center Width, Height, Width



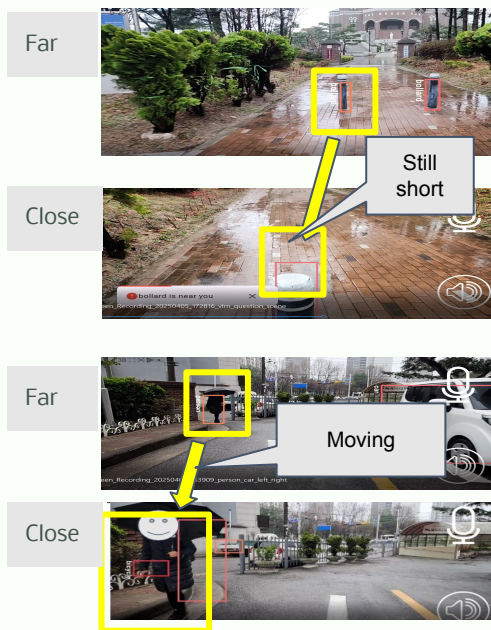
Warning Mode (Be careful)

- Parameter: Center Width, Height, Width, Top, Bottom



Challenges

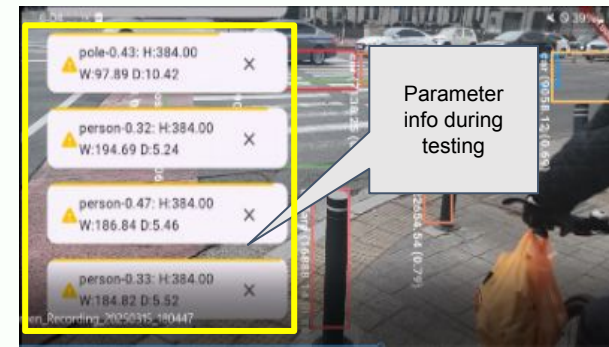
Uniform parameter conditions are not applicable, as each class differs in relative size –from short (bollard) to tall (tree), wide (car), and dynamic objects like moving persons.



Approaches

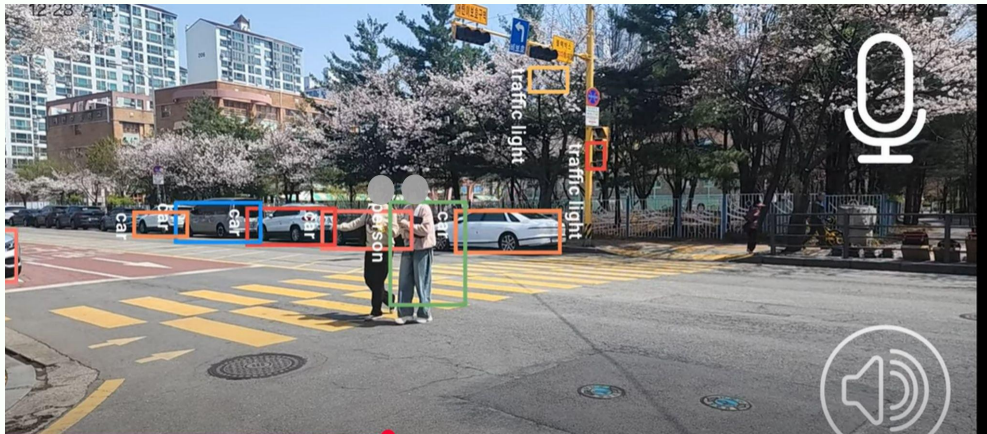
Extensive testing and iterative adjustments with debugging test mode and as we classified test images for each class, configured parameter conditions

<Test Mode>



Find the Model that Best Explains Scenes to Users

VLM Evaluation- Example



Q: Please describe what is in front of me

Paligemma's description:

"The image is a video of a crosswalk with a person and a car in the middle of the road."

Qwen2's description:

"The image shows a city street scene during the day time. There are several people crossing the street at the pedestrian crossing marked with yellow line. The street is relatively wide and has a few cars parked along the side. There are trees with blooming flowers likely cherry blossoms..."

Model	Navigation Safety (Score & Explanation)	Spatial Orientation (Score & Explanation)	Environmental Awareness (Score & Explanation)
Paligemma	2.5/5 <ul style="list-style-type: none">• Mentions person & car in road• Vague on safety context	1/5 <ul style="list-style-type: none">• Only says "crosswalk"• No layout or direction	1/5 <ul style="list-style-type: none">• No weather/time info• No surroundings
Qwen2	3/5 <ul style="list-style-type: none">• Notes pedestrian crossing• Mentions people walking	4/5 <ul style="list-style-type: none">• Describes street & parked cars• Mentions crosswalk & layout• Good scene structure	3.5/5 <ul style="list-style-type: none">• Mentions trees & cherry blossoms• Notes daytime setting• Adds calm ambiance

WIN!

VLM Evaluation- Overall Result



Model	Navigation Safety	Spatial Orientation	Environmental Awareness	Overall
Goal	Identify hazards, obstacles, and safe paths	Help users build a mental map	Context about surroundings for navigation decisions	—
Paligemma	3.0	2.1	2.2	2.4
Qwen2	3.9	3.8	3.9	3.9
Gap	+0.9	+1.7	+1.7	+1.4

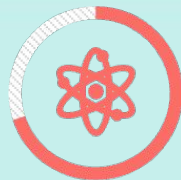
WIN!

Qwen 2

vs

Paligemma

Evaluated using 30 real-world urban scene



4-6x

67% better performance across all metrics

more detailed descriptions

(avg. 65-70 words vs. 11-12 words)

Find the Model that Best Explains Scenes to Users



Metrics on VLM captions evaluation

Compare text similarity between human descriptions and model generated descriptions

	ROUGE			METEOR
	Rouge 1	Rouge 2	Rouge L	Meteor
Qwen2 WIN!	0.40	0.15	0.27	0.36
Paligemma	0.21	0.07	0.16	0.20

Sample: 30 images from 12 different cities in 7 countries

ROUGE: Share of overlapping words and phrases of different lengths between human descriptions and model descriptions

METEOR: Harmonic mean of unigram precision and recall, with recall weighted higher than precision



Key Achievements



Customized model

- New classes on outdoor objects with large training datasets
- High accuracy at relatively reasonable training costs



Informative alerts

- Box-boundary based alerts
- Additional colors on the position of objects
- Combined with VLM for detailed descriptions



Efficient deployment

- Yolo model deployed **on-device** to reduce latency
- VLM model via **API**



Next Steps: Expand Vision Capability



Expanding OS Compatibility

Finalize a version of the App for IOS system



Alert Rule with ML Classification Model

Use machine learning method to optimize alerts based on the object and screen size of users' devices



Expanding Global Services

Customize object detection models for specific countries or cities
Enhance multilingual services (Quick Spanish demo)



Wearable Device Integration

Connect with wearable cameras such as Go-Pro, Insta360 Go3, for hands-free options
Look for more cost-efficient solutions



A World Equally Accessible to All



Our Problem

Difficulty of visually impaired individuals when navigating outdoor



Solution: SafeWalk

App that uses object detection and Visual-Large Language models to describe situations and give audio alerts



Our Mission

Empower visually impaired individuals with the safety, independence, and confidence to navigate the world!

Our Website

<https://zhangke626.github.io/safewalk-website/>