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Integrated Assistive System for Precise Indoor Navigation, Object Recognition, and Interaction for Visually Impaired Individuals

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***Abstract* - Indoor navigation poses significant challenges for those with visual impairments. To address this, an integrated system is proposed, aiming to empower visually impaired individuals by enhancing their indoor navigation and object recognition capabilities, ultimately promoting independence and safety. This innovative system amalgamates cutting-edge technologies such as IoT, deep learning, and machine learning. It incorporates IoT for real-time object detection, precise distance estimation, and collision avoidance features, ensuring users are well-informed about their surroundings. Moreover, the system employs a Wi-Fi-based indoor positioning system, combining machine learning algorithms and triangulation techniques to provide accurate indoor localization data, a critical component for effective navigation. To further enhance user experience, an audio assistant integrated into a mobile application leverages machine learning. This assistant delivers real-time guidance, object descriptions, and contextual information, enabling users to interact naturally with the system. This comprehensive research paper thoroughly explores the system's components, the underlying technologies that power it, and the results of comprehensive evaluations. It holds the promise of significantly improving the indoor navigation experience and quality of life for individuals with visual impairments.**

Keywords: Internet of Things, Indoor Positioning, Object Detection, Path Planning.

I. INTRODUCTION

Individuals facing visual impairment encounter formidable challenges when navigating indoor spaces, as their capacity to recognize visual cues and impediments is constrained, compromising their independence and safety. In order to address these difficulties, this research proposes an integrated system that incorporates motion planning algorithms, machine learning, IoT-driven deep learning, and natural language processing. The ultimate goal is to craft an efficient system for recognizing objects and aiding navigation within indoor environments, tailored to the unique needs of visually impaired individuals. Accurate object recognition emerges as a pivotal factor in ensuring secure navigation. The proposed system capitalizes on an IoT-powered deep learning framework, proficiently detecting objects and providing precise distance estimates. By harnessing advanced neural networks and high-resolution cameras, the system adeptly identifies various objects within the indoor setting, enhancing users' environmental awareness and bolstering their confidence in navigation.

In addition to object recognition, the system encompasses crucial functionalities such as path finding and collision avoidance within indoor spaces. This is seamlessly achieved through the incorporation of motion planning algorithms. These algorithms exhibit dynamic obstacle detection capabilities and chart routes that are free from collisions, thus enabling visually impaired individuals to navigate intricate indoor layouts with heightened efficiency and reduced risk.

The precision of indoor positioning is fundamental to effective navigation support. To meet this need, the suggested system incorporates triangulation methods, machine learning algorithms, and an indoor location system based on Wi-Fi. This system reliably calculates the user's position within the indoor environment by utilizing existing Wi-Fi infrastructure, providing real-time positioning updates that permit efficient navigation to planned destinations.

The use of an audio assistant within a mobile application enhances the navigating experience further. This audio assistant uses machine learning and natural language processing to give audible assistance that includes object descriptions, navigational instructions, and contextual information that is specifically adapted to the user's location and objects that have been spotted. This function encourages

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improved connection and communication between people with visual impairments and their environment, ultimately encouraging more independence in interior navigation.

This paper essentially introduces a system that combines deep learning, motion planning algorithms, machine learning powered by the Internet of Things, and natural language processing. By efficiently implementing these technologies, it is intended to empower people with visual impairments and improve their capacity to maneuver in enclosed spaces.

II. LITERATURE REVIEW

The 2017 paper [1] aimed to help visually impaired individuals navigate indoors using computer vision focusing on enhancing object detection by combining detection scores effectively. The method analyzed indoor webcam image frames and used two advanced deep learning algorithms, SSD and YOLO, for object detection. Scores for various object categories were merged using the Proportional Conflict Resolving principle. The object with highest score was selected, and the audio information was transmitted to the user through wearable headphones.

In a research paper published in 2022 [2] the authors present innovative approach for identifying indoor home environment. They used a Mask-RCNN for accurate item detection and a Convolutional Neural Network (CNN) to identify scenes. CNN was fed with the output from the Mask-RCNN to improve object recognition within particular scenes. The CNN was trained using 500 different combinations of five different interior scenarios produced by Mask-RCNN. The obtained results were impressive in that they showed an astounding 97.14% accuracy for the outcome.

In [3], the authors present an integrated framework, merging Convolutional Neural Network-Recurrent Neural Network (CNN-RNN), for accurate environmental sound classification. To combat data scarcity, they leverage a Deep Convolutional Generative Adversarial Network (DCGAN) to augment the dataset by generating spectrograms resembling the original training set. By combining real and generated data inthe CNN-RNN model, they show improved performance in environmental sound classification. This novel approach outperforms existing state-of-the-art methods, as validated on the UrbanSound8K dataset.

Early studies on Wi-Fi-based indoor positioning focused on fingerprinting methods, which call for compiling a database of signal strength readings from various points across a building. After that, the user's location is determined by comparing current signal strength readings with this database. The "RADAR" method by Bahl and Padmanabhan [4], which pioneered the idea of indoor localization using fingerprints of received signal strength (RSS), is a noteworthy piece of work.

The use of trilateration-based algorithms, which locate the user by traversing circles (or spheres in 3D), depending on signal propagation delays or signal strengths, has also been thoroughly studied. Understanding the locations of Wi-Fi access points is necessary for this method. Important research, like Hightower and Borriello's work [5], showed the viability of trilateration-based techniques and highlighted issues with signal fluctuations and multipath. The "BLocate" technique was introduced by Ashraf, Hur, and Park in 2018 [6]. It makes use of smartphone sensors in locations where GPS is not available to identify buildings. They show that, even in the absence of conventional GPS signals, smartphone sensor data can be used to provide indoor positioning.

Ashraf, Hur, and Park (2019) built on their earlier research by investigating indoor positioning utilizing Wi-Fi access point coverage areas on several commercial cellphones [7]. This study emphasizes how Wi-Fi signals can be tailored to different smartphone platforms for indoor positioning.

To increase accuracy and resilience, Wi-Fi-based indoor positioning systems are increasingly combining machine learning algorithms. To improve position estimation based on Wi-Fi fingerprints, researchers have utilized techniques including k-nearest neighbors, support vector machines, and neural networks [8]. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), two deep learning approaches, have been studied recently to automatically learn complicated spatial patterns from Wi-Fi signals [7]. To increase accuracy and resilience, Wi-Fi-based indoor positioning systems are increasingly combining machine learning algorithms. To improve the localization based on Wi-Fi fingerprinting, researchers have combined techniques including k-nearest neighbors, support vector machines, and neural networks [8]. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are two deep learning techniques that have recently been investigated in literature to automatically learn complex spatial patterns in Wi-Fi data [7].

Map creation is an essential component of autonomous robot navigation. In recent years, there have been numerous advances in the field of mapping, with new techniques being developed for accurately representing the environment in real-time. One of the most popular mapping techniques is Simultaneous Localization and Mapping (SLAM) [9], which involves using sensor data to create a map of the environment while simultaneously localizing the robot within that map. SLAM has been used in a variety of settings, including warehouse automation, self-driving cars, and robotics research.

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When it comes to collision avoidance, optimization-based collision avoidance [10] is a crucial subject. The strong duality of convex optimization is used in this paper to present a unique method for transforming smooth nonlinear constraints from non-differentiable collision avoidance needs. In order to avoid obstacles, the study focuses on a controlled object moving across an n-dimensional space. Any controlled barriers and objects that may be represented as the union of convex sets without introducing approximations are covered by the suggested change.

Indoor navigation poses significant challenges for people with visual impairments, often relying on costly assistive devices. Addressing this, a wearable system, detailed in study [11], merges computer vision and motion planning. Comprising a camera, embedded computer, and haptic device, it alerts users to obstacles. The system identifies traversable areas, plans safe routes, and recognizes objects like empty chairs, relaying this information through haptic vibrations. User studies encompassing various tasks, from navigating mazes to finding chairs in crowded spaces, underscore the system's potential. It offers an affordable means to enhance mobility and situational awareness for visually impaired individuals, mitigating the expense barrier associated with assistive technologies.

A research paper titled "A Smart Personal AI Assistant for Visually Impaired People" by Shubham Melvin Felix, Sumer Kumar, and A. Veeramuthu [12] presents a smart personal AI assistant called "VizAssist" designed to assist visually impaired people in their daily activities. The proposed system uses computer vision and natural language processing techniques to provide audio feedback to the user. The system is designed to recognize objects, text, and faces, and provide the user with the relevant information. The system can also assist the user in reading books and identifying currency notes. The authors claim that the system is low-cost and can be easily integrated with a smartphone. The paper is a recent contribution to the field of assistive technology for visually impaired people. The proposed system is similar in some aspects to other systems presented in the literature, such as the "Seeing AI" app by Microsoft and the "Be My Eyes" app. However, the authors claim that their system has some unique features, such as the ability to recognize currency notes and read books aloud.

III. RESEARCH PROBLEM

The research problem addressed in this study lies at the intersection of technology, accessibility, and human well-being. It centers on the challenges faced by visually impaired individuals when navigating complex indoor environments. Despite significant advancements in assistive technology, the indoor space presents a unique set of obstacles that hinder independence and mobility for this community. Traditional tools like white canes and guide dogs excel in outdoor settings but fall short when it comes to maneuvering through indoor labyrinths filled with dynamic obstacles and ever-changing layouts.

This research problem seeks to bridge this gap, aiming to create a comprehensive assistive system that not only provides precise indoor navigation but also empowers users with real-time object recognition and interaction capabilities. Indoor spaces are intricate ecosystems where a multitude of challenges converge. For the visually impaired, the absence of natural landmarks, unfamiliar layouts, and unexpected obstacles can make even the simplest indoor tasks daunting. Basic activities like finding a chair, avoiding a table, or locating a restroom stall can become arduous undertakings.

The complexity of indoor environments extends beyond navigation; it encompasses the ability to interact with objects and elements in the surroundings. Recognizing a door, distinguishing between elevators and stairs, or identifying an empty seat in a crowded cafeteria are tasks that sighted individuals often take for granted but present profound hurdles for those with visual impairments. Therefore, the research problem underpinning this study transcends mere way finding; it delves into the realm of object recognition and interaction within indoor spaces.

IV. METHOLOGY

The proposed system integrates with four main components to assist in indoor navigation for visually impaired individuals. The four components are as follows.

- Indoor Positioning System Utilizing Wi-Fi with Machine Learning and Triangulation Algorithms.
- Real-Time Object Detection and Distance Estimation enabled by IoT and Deep Learning.
- Utilizing IoT Technology and Motion Planning Algorithms for Pathfinding and Collision Avoidance.
- Voice recognition and Voice Assistance Sub System to Deliver an Audio Feedback to the visually impaired.

3.1 Object Detection Model

This aims to develop an object detection model using TensorFlow specially for the use of Raspberry Pi camera. The goal is recognizing regular and hazardous objects and improving awareness and safety in practical situations.

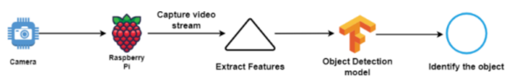

Figure 1: How to get result from trained model

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3.1.1 Collect Data and Label Images

To train the model for object detection, gathered images from a popular image dataset called COCO. These images underwent careful labeling to provide effective supervision throughout the model training process.

3.1.2 Development

The object detection was split into two – identify regular objects and identify hazardous objects. Pretrained TensorFlow models from the TensorFlow Model Zoo explored to develop precise and effective model. After a comprehensive evaluation on various models on the dataset, the ssd_mobilenet_v2_fpnlite_320x320_coco17_tpu-8 model was chosen for its superior performance over other options.

3.1.3 Training Model

Trained the selected model using a labeled dataset that includes over 7000 images. To enhance model performance and accuracy set batch size of 32 and configured 30000 training steps.

3.1.4 Evaluation Model

Assessed model's performance in the testing phase. It effectively detected objects across diverse scenarios. Demonstrating its ability to detect regular and harmful objects accurately, underlining the effectiveness of the created object detection system.

Figure 2: Detect Harmful Object

3.2 Recognize Indoor Scenes

Recognition of indoor environment is a crucial role of assisting individuals with visual impairments to comprehend their surrounding environment.

3.2.1 Data Gathering and Data Preprocessing

In developing the model, utilize a sizable dataset called MIT Indoor Scenes. Each category was comprised of a collection of 2000 images, which were then segregated into train and test sets.

3.2.2 Model Development and Training

The model was built using transfer learning, a powerful deep learning technique. In order to solve the scene identification task, MobileNetV2 and VGG16, two pretrained models, were integrated with a Convolutional Neural Network (CNN).

3.2.3 Balanced Dataset with VGG16

Created a balanced dataset designed for training the VGG16 model to reduce overfitting. Even though the model's testing accuracy was 93.33%, its predictions were wrong, leading to incorrect results.

3.2.4 Dropout Layer with MobileNetV2

The balanced dataset was then used to train the MobileNetV2 model once more, this time adding a dropout layer for improved generalization. In the final analysis, this improved model had an accuracy of 89%.

3.3 Object Detection with Audio Classification

The technology for audio-based object detection uses sound signals to identify and pinpoint diverse items, presenting several benefits compared to conventional vision-based identification methods. This method allows the detection of objects that are not visually evident or else easily identifiable through alternative approaches.

3.3.1 Data Gathering and Model

With the aim of assisting people with visual impairments in identifying the presence of various items or entities in indoor contexts where visual based detection encounters difficulties, the dataset ESC-50 was used to construct the model for object identification based on sound.

3.3.2 Training Model – CNN and YAMNet

Employed a Convolutional Neural Network (CNN) initially and trained it with a 70% accuracy. The YAMNet pretrained TensorFlow model, which significantly increased accuracy to 76.49%, was included to the system, however, to boost performance.

3.3.3 MFCC – Extract Features

Implemented the Mel-Frequency Cepstral Coefficients (MFCC) feature extraction method on audio files to enhance the model's functionality. The model can achieve a higher level of accuracy thanks to this method's ability to capture important sound features. The final model was chosen due to its excellent performance and suitability for the intended

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usage, and it combined MFCC elements to attain an accuracy of 76%.

3.4 Distance Estimation

An HC-SR04 ultrasonic sensor, measure distance by emitting a brief 10-milliseconds pulse using the trigger, which travels as an audio signal. This audio signal reflects off a surface and the sensor detect it back. Measuring the time, it takes for the audio signal to travel from the sensor to the surface and get back allows an estimation of the distance to the object.

The speed of sound in the air is approximately 343 meters per second, is halved in the calculation since the audio signal covers the same distance twice (to object and back),

The distance can be calculated using the formula:

$$\text{Distance} = \text{Time} * (\text{Speed of Sound} / 2)$$

Given the speed of sound is 34300 cm/sec, the distance can be expressed as:

$$\text{Distance} = \text{Time} * 17150$$

By plugging measured time into this formula enables an accurate estimation of the distance.

3.5 Indoor Positioning Based on Wi-Fi

3.5.1 System Overview

The Wi-Fi-operated indoor positioning system used in this work has two basic phases: calibration and positioning. Figure 4 shows these stages in detail. The system examines and records the Wi-Fi access point Radio Signal Strengths (RSS) at various locations across the structure during the calibration phase. The server database is then updated with this data. The technique uses RSS values from an undisclosed place to estimate the user's position during the positioning phase.

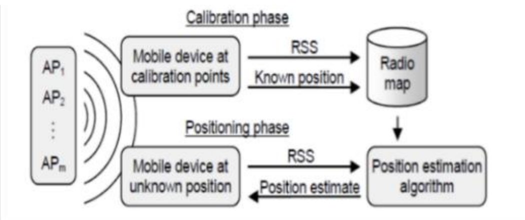

Figure. 3: Overview Diagram

3.5.2 Location Fingerprinting

By comparing the varied signal intensities obtained from various routers, location fingerprinting is used to differentiate between different sections of the building. Each particular place is uniquely identified by the received signal intensity. Several locations inside the structure are picked during the calibration phase, and the recorded RSS values from various access points are gathered. The radio map, which is represented as a tuple, is created from each of these measurements.

$$(l_i, s_i) \quad i = 1, 2, \ldots n$$

$$\text{where } l_i = (x_i, y_i)$$

designates the location's geographic coordinates and

$$s_i = (s_{i1}, s_{i2}, \ldots, s_{im})$$

specifies the RSS values from m nearby access points.The coordinates of RSS data that are gathered from an unfamiliar area during the installation phase are estimated using the current radio map as a reference.

3.5.3 Weighted K-Nearest (WKNN)

The Weighted k-Nearest Neighbors (WKNN) method was chosen as the algorithm for calculating location. There are two essential steps in this strategy:

3.5.3.1 Finding the K nearest neighbor in the radio map

Input: Set of all n readings from the calibration phase,

$(l_1, s_1), (l_2, s_2), \ldots, (l_n, s_n)$,

and the reading from the current unknown location, r.

Output: Set of k nearest points.

Procedure: The n points are arranged in ascending order of Euclidean distance from the current reading, s, for the n points. The readings are analyzed as vectors to get the Euclidean distance. The sorted list's first k readings,

$(l_1, s_1), (l_2, s_2), \ldots, (l_k, s_k)$

are returned as the k nearest points.

3.5.3.2 Calculating the coordinates of the current unknown location

Input: Set of k nearest points,

$(l_1, s_1), (l_2, s_2), \ldots, (l_k, s_k)$.

Output: Coordinates of the current unknown location.

Procedure: The coordinates are calculated using the formula:

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$$l = \sum_{j=1}^{k} \frac{w_j l_j}{\sum_{l=1}^{k} wf(x)=w_1}$$

where all weights are nonnegative,

$$w_j = d^{-1}{}_{(si,\, s)}$$

d represents the Euclidean distance between the readings, and lj denotesthe coordinates of the jth location.

The WKNN algorithm's tuning parameter (k), which controls how many nearby neighbors are considered while determining a location, controls how local the calculation is. For k = 1, the method operates as a conventional look-up table, but for larger numbers, it predicts that the position will be somewhere between the calibration points.

The suggested system may estimate the user's position based on the recorded RSS values and the radio map created during the calibration phase by utilizing the calibration and positioning phases, as well as the WKNN algorithm.

For indoor applications like localization and autonomous navigation, building precise radio maps is crucial. Wi-Fi networks that are too many and irrelevant provide problems for current approaches, resulting in time-consuming procedures and inaccurate maps. This study suggests a novel strategy that makes use of a strong filtering mechanism that locates users' router SSIDs for selective inclusion of Wi-Fi networks. This completely transforms the creation of radio maps and greatly enhances efficiency and accuracy. This technology simplifies mapping and improves the functionality of indoor location-based applications overall.

3.6 Pathfinding and Collision Avoidance

3.6.1 System Overview

The suggested method takes advantage of the A* algorithm's potency to address the complexities of pathfinding in indoor situations. This technology captures the essence of the environment by seamlessly integrating a Pi camera, finally transforming it into a grid that can be navigated. The solution computes the shortest path between predetermined start and end nodes and is effective and collision averse.

The Pi camera and the A* algorithm work in perfect harmony thanks to this system. Real-time picture acquisition is the first step in the procedure, which is then processed, segmented, and grid generated. The best path is then dynamically determined by the A* algorithm, which avoids obstacles indicated by binary grid cells with values of 1. With the potential to address the complexities of real-world situations and pave the way for breakthroughs in robotic mobility, this integrated method represents an innovative and effective solution for autonomous indoor navigation.

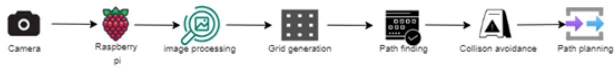

Figure 4: How get output of A* algorithm

3.6.2 Map Creation

The methodology proposed in this section of the study presents an innovative solution to indoor pathfinding and enables precise and effective navigation inside difficult interior circumstances by smoothly integrating the A* algorithm with image-based grid mapping. The main objective is to use the camera of a Raspberry Pi to take real-time pictures of the environment, analyse those pictures, and then use the navigable grid they produce as input for the A* algorithm. The accuracy and utility of interior navigation scenarios are expected to be enhanced by this comprehensive system.

The methodology consists of a number of crucial phases that when used together make it easier to integrate image processing, grid mapping, and A* pathfinding. Using the camera module of the Raspberry Pi, the first step in the procedure is to take pictures of the indoor surroundings. Preprocessing techniques are then used on the collected photos to improve their quality and lower noise, assuring optimal performance throughout the methodology.

The proposed images are then transformed into a grid representation, which forms the basis of the A* algorithm, in the following phase.

Figure 5: created grid map base

Through an image segmentation procedure, the environment is divided into discrete cells based on distinctive visual elements within the photographs, and this conversion is made possible. These characteristics could consist of barriers like walls and open areas. The grid representation is made up of attributes that are allocated to each cell, such as traversal cost, connectedness to nearby cells, and obstacle presence.

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3.6.3 Path planning and Collison Avoidance

The A* algorithm for pathfinding is then used after the grid has been established. The grid's characteristics, including traversal cost and connectivity, are taken advantage of by the A* algorithm to identify the best route between the defined start and finish nodes. The pathfinding procedure aligns with the physical architecture of the environment thanks to the combination of the A* algorithm and the image-based grid mapping, which minimizes the risk of collision with obstacles and maximizes efficiency.

This integrated methodology's ability to adjust to environmental changes occurring in real time is a major benefit. The grid representation can be dynamically changed to take into account for moving impediments or environmental changes because the Raspberry Pi continuously takes pictures. This responsiveness guarantees that the pathfinding process will continue to be precise and trustworthy.

```
Please say the object you want to reach:
You want to reach: TV monitor

Path to the TV Monitor
Cell: (5, 5)
Cell: (5, 4)
Cell: (6, 4)
Cell: (6, 3)
Cell: (7, 3)
Cell: (7, 2)
Cell: (8, 2)
```

Figure 6: generated path based on the grid map

3.7 Voice recognition and Voice Assistance to Deliver an Audio Feedback to the visually impaired

The primary objective of this component is to facilitate seamless interaction between visually impaired individuals and the system via voice commands, leveraging the capabilities of natural language processing techniques. Unlike sighted users who can interact with mobile devices through touch screens, visually impaired individuals face unique challenges due to their reliance on auditory cues. Therefore, the methodology employed herein focuses on developing an inclusive solution that empowers visually impaired users to effectively communicate with the system using voice commands. By harnessing the capabilities of natural language processing, the system aims to interpret these voice inputs accurately and translate them into actionable instructions, enhancing their engagement and navigation experience within the system.

The initial step involves capturing voice commands from users through the mobile device's microphone. These voice inputs are then subjected to a comprehensive processing pipeline that combines natural language processing techniques with TensorFlow. TensorFlow aids in the analysis and interpretation of the voice commands, allowing the system to understand user intentions accurately through this fusion of voice analysis and machine learning.

Simultaneously, the system employs a Raspberry Pi, to perform real-time object detection through the device's integrated camera. Detected objects are subsequently processed, and relevant information is collected. Additionally, path planning components gather pertinent spatial data to contribute to the user's navigation experience. These parallel processes serve as crucial data sources for the ensuing audio guidance mechanism.

Integration of the voice command analyses, object detection results, and path planning data culminates in the creation of a coherent and meaningful voice assistant. This voice assistant is meticulously designed to provide navigation assistance to visually impaired users. By harnessing the power of natural language processing and TensorFlow analysis, the system generates personalized audio instructions that guide users through their surroundings.

The blending of voice command processing, TensorFlow analysis, object detection, path planning, and audio guidance forms a strong solution that helps visually impaired individuals move around indoors. This thorough combination doesn't just solve the immediate problems of moving indoors, but also adds to the overall improvement in the lives of visually impaired users by giving them more independence.

In summary, the method we've described provides a strong structure for building the system we propose. By bringing together voice commands, NLP, TensorFlow, object detection, path planning, and audio guidance, we've created an innovative and effective way for visually impaired individuals to navigate, making a positive impact on their lives.

V. CONCLUSION

In conclusion, this study work offers a thorough and original solution to the problems that visually impaired people encounter when navigating indoor spaces. A complex solution is provided by the combination of IoT, deep learning, machine learning, indoor positioning methods, and aural aid via a mobile application. This comprehensive strategy improves auditory guidance while also improving object detection, exact distance calculation, pathfinding, collision avoidance, and accurate indoor localization. The system has the potential to considerably enhance the quality of life for those who are visually impaired, as demonstrated by the efficient deployment and evaluation of these components. By including audio aid, it provides not only more independence and safety but also a more open and enjoyable interior experience.

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