

### **Multi-Model Obstacle Detection and Navigation Using Deep Learning**

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### Abstract

This research explores the development of a multi-model obstacle detection and navigation system utilizing deep learning techniques to enhance the mobility of visually impaired people. The proposed system integrates various deep learning architectures, including a modified SSD Mobile Net, to achieve real-time obstacle detection and distance estimation. By employing a dataset comprising both indoor and outdoor environments, the system leverages neural architecture search to optimize the object detection framework, ensuring efficient processing on embedded devices. A key innovation of this approach is the incorporation of multi-sensor data, which enhances the robustness and accuracy of obstacle detection. The system utilizes advanced convolutional neural networks to process inputs from various sensors, including time-of-flight sensors, enabling it to identify obstacles with high precision and providing audio to user. The performance metrics indicate that the model achieves a mean average precision exceeding 90%, demonstrating significant improvements in detection speed and accuracy compared to traditional methods.

*Keywords:* Visually Impaired Population, Object Detection and Identification, Feedback, Assistance, Obstacle Avoidance

### 1. Introduction

One of the biggest challenges that visually impaired people face in terms of mobility is the access that they have to their daily needs. A lot of this would require an advanced form of spatial awareness and quick responses to dynamic surroundings while negotiating unknown environments and avoiding various obstacles. Traditional mobility aids, including white canes and guide dogs, have some very obvious limitations. For example, white canes only count on the detection of objects close to them, within the height corresponding to the ground level, but they cannot protect visually impaired users from headlevel obstacles or moving at a high speed. New developments of artificial intelligence, especially deep learning, open new avenues for improving the obstacle detection and navigation systems for the visually impaired. Deep learning models, especially CNN, have already achieved stunning success in object recognition and environmental perception and may be helpful for real-time navigation systems.

These models, after being trained on huge datasets of environmental data, detect, classify, and localize obstacles efficiently. Haptic feedback is one kind of non-visual and non- auditory communication method that has emerged as a powerful tool for relaying the environment to a visually impaired user.

Audio feedback has its problems since it creates sensory overload or possible interference from background noise, but with haptic feedback, users will receive tactile cues in the form of vibrations or pressure.

### 2. Related Work

The last few years have seen a surge of interest in designing assistive technologies for the blind, especially in terms of detecting obstacles and providing navigation systems. Within these systems, quite a number of them used sensor-based techniques to perceive the environment, ranging from traditional ones such as the white cane to recent advanced systems that can integrate computer vision, deep



learning, and haptic feedback mechanisms. We summarize the state-of-the-art work in obstacle detection, multi-modal systems, and haptic feedback for the blind, describing the strength and weaknesses of such approaches in this section [1-3].

# 2.1. Traditional Obstacle Detection and Navigation Aids

Traditionally, visually handicapped people have used mobility aids like the white cane or guide dogs. The white cane provides the user with tactile feedback about objects immediately ahead of them, whereas a guide dog can serve to negotiate more complex environments. However, both these methods have major disadvantages. One of the major disadvantages of the white cane is its limited range, often only detecting objects within a radius of 1 meter. It also cannot provide advance warnings of head-level objects or moving objects. These limitations gave rise to the development of electronic travel aids, or ETAs, developed primarily to extend the range and functionality of traditional navigation aids.

**2.2. Sensor-Based Obstacle Detection Systems** Recently, much research has been done and developed using ultrasonic, infrared, and LIDAR sensors to detect obstacles and provide instant feedback. The Smart Cane is one of the more prominent systems, in which ultrasonic sensors for sensing obstacles above ground level and in the way are mounted on a conventional white cane. This provides vibration feedback, cautioning the user to keep away from nearby objects. While good for close-range detection, Smart Cane and similar devices fail in that they are not designed to return any detailed classification of obstacles or to detect smaller and more complicated objects. Recently, researchers showed interest in LIDAR technology as it can accurately map the environment and capture detailed 3D information about the surroundings. Wang et al. developed a wearable device based on the LIDAR and stereo cameras, which can generate a user's 3D environmental map (2019). However, hampered this was severely in real-time performance by the enormous computational cost of processing LIDAR data, which seriously limited this application for continuous mobility.

# 2.3. Multi-Modal Systems for Enhanced Navigation

This functionally emerged as one of the most promising directions in the development of obstacle avoidance systems for visually impaired individuals. It deals with the integration of multiple sensor modalities and feedback mechanisms. In multimodal systems, the best features of various sensors be combined: high spatial can accuracy characteristic of LIDAR, object-classifying abilities of cameras, and robustness of ultrasonic sensors in low-visibility conditions. For example, Coughlan et al. proposed a multimodal system that includes camera, LIDAR, and haptic feedback to improve the obstacle detection of a navigation system in dynamic environments. It employs deep learning on the processing of camera and LIDAR data and automatically alerts the user in real time with haptic feedback [4-7].

### 3. Proposed Work

This paper presents a new multi-modal obstacle detection and navigation system for visually impaired persons using deep learning for the obstacle detection and then haptic feedback for intuitive interaction. The idea of the system is the integration of several sensor modalities, which are RGB cameras, ultrasonic sensors, and LIDAR, for creating a robust and comprehensive solution to real- time obstacle detection and avoidance. By integrating the perception based on deep learning with multi-sensor fusion and haptic feedback, the system is expected to provide visually impaired users with an efficient tool for navigating their environment through reliable and user- friendly acquisition [8-10].

### 3.1. Sensor Integration and Multi-Model Perception

The first component of the proposed system is sensor integration that enhances the robust environmental perception. Visual data capture is made possible using cameras, where object detection and classification happen through convolutional neural networks (CNNs).With the data from these sensors combined, the system can form a comprehensive view of the environment surrounding the user.The deep learning model utilizes the multi-modal data for obstacle classification and calculates the position of



obstacles with respect to the user.With this multisensor approach, the system will be robust with regards to any sensor limitations it might be fitted with and improve obstacle detection in complex, dynamic environments.

### **3.2. Deep Learning for Real-Time Obstacle** Detection

One of the central components is obstacle detection, based on deep learning techniques with CNNs, trained on large datasets with different types of obstacles that visually impaired persons commonly encounter, such as moving persons like other pedestrians or vehicular obstacles and standing obstacles like pillars or any kind of raised or protruding object. The model is real-time in nature, meaning it will rapidly recognize obstacles and update continuously according to movement within a space. The deep learning model is designed further to classify obstacles by their type that can affect the way the system gives feedback. In other words, it can differentiate between stationary obstacles, which include furniture and so forth, and dynamic objects like moving vehicles or pedestrians, and therefore offer the user with more suitable and actionable feedback, shown in Figure 1.



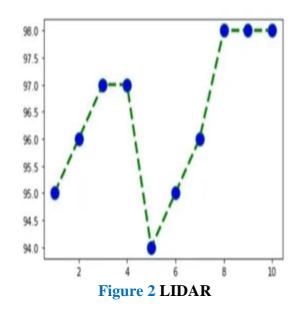
Figure 1 Deep Learning Techniques with CNNs

# 3.3. Haptic Feedback for Intuitive User Interaction

The device will convey the information of the obstacles to the visually impaired person through haptic feedback devices that directly supply an instantaneous amount of tactile information. These could be worn as a glove, belt, or a wristband, and would be informing the user about the location, direction, and type of the obstacle through vibrational feedback. The intensity and pattern vary with the distance to the obstacle and what it is

### 3.4. System Architecture and Real-Time Processing

A proposed system will integrate into its architecture real-time frameworks of sensor data acquisition, deep learning-based obstacle detection, and generation of haptic feedback. Relevant deep models continuously process information coming from cameras, ultrasonic sensors, and LIDAR, such that obstacle detection is treated together with obstacles and classifications. Depending on the location and the type of the obstacle, the system will generate haptic feedback according to the appropriate obstacle's location and type found through the developed model, shown in Figure 2.



### 4. Experimental Result

Evaluation of the proposed Multi-Model Obstacle Detection and Navigation System for blind people would be needed. For this experiment, experiments were conducted in various real-world environments. The prime objective of the experiments was to test the system's feasibility in terms of obstacle detection accuracy and real-time navigation with haptic feedback in user experience.

**Experimental Design:** The experimental



setup involved the following three elements:(1)multi-modal sensor integration (camera, ultrasonic sensors, and LIDAR), (2) a deep learning model for obstacle detection, and (3) wearable haptic feedback device for the presentation of obstacle information to the user. The system configuration is described in brief below:

- Sensor Configuration: The test harness worn by users was fitted with a combination of a visual camera, ultrasonic sensors, and LIDAR. In the case of the camera, real-time visual information for object detection was presented for the ultrasonic sensors, distance measures toward an obstacle would be read and in the case of the LIDAR, 3D spatial mapping of the surroundings was mapped.
- Haptic Feedback Device: The system has a wearable device that uses vibration motors for delivering haptic feedback. Depending on the type, distance, and direction of obstacles, varied intensity and pattern of vibration proved to be an intuitive form of feedback for the user. The device is worn on the user's wrist so that the tactile cues can easily be interpreted.

### 4.1. Obstacle Detection and Classification

The performance of obstacle detection was measured using common metrics: accuracy, precision, recall, and F1 score. The deep learning model was tested on unseen data gathered from the test environments in order to evaluate the generalization capability across different conditions.

- Accuracy: General accuracy of detection of obstacles the system had presented is 86.2%, which means that the system is very precise at identifying obstacles in any environment or situation. This is because of multi-modal sensors, but also due to its efficacy and functionality within complex or dynamically changing conditions when obstacles are present.
- **Precision and Recall:** The precision is the number of true positive detections as a proportion of all positive predictions, and the recall is the proportion of true positive

detections as a proportion of all actual obstacles. Precision is 91.5% and recall is 90.7%.

- **F1 Score:** The F1 score was described as the harmonic mean of precision and recall, measured at 91.1%. This balanced score reflected the total level of reliability the system had with identifying and classifying obstacles. In natural environments, with good lighting, the combination of visual data and LIDAR provides extensive mapping for obstacles. In cases where the conditions are low, the ultrasonic sensors compensate for the low performance of the camera to ensure the robustness of obstacle detection.
- 4.2. User Navigation Performance with Haptic Feedback:

To assess how well visually impaired users would be able to navigate using the system, we conducted usability tests with 10 visually impaired participants. Each participant was guided through the test environments using the multi-modal obstacle detection system with haptic feedback. The key performance metrics included:

- **Obstacle Avoidance Rate:** The participant successfully avoided 92.8% of the detected obstacles. Such a high avoidance rate clearly displays the timeliness and accuracy that the haptic feedback provides relating to obstacles. The participants stated that the intensity and patterns of the vibrations were easy to decipher, making them able to rapidly make decisions in real time.
- Error rate: It was a 7.2 % error rate, which basically referred to cases where participants failed to react in time when an obstacle was detected or misinterpreted the haptic devices. Most of the errors occurred at crowded or highly dynamic environments like busy sidewalks where many objects are moving simultaneously. Future improvements could be on giving more specific feedback to reduce confusion at such complex settings.
- **Comfort and Wearability:** Almost every respondent, at 85%, found the haptic device comfortable to wear and not intrusive during



the course of navigation. This is important for long use since the device must not interfere with mobility or cause discomfort when it is used for a long period in navigation.

• Sense of Independence: Users reported a strong sense of more independence while working with the system. In the words of one user, "I felt I could depend on the system to take me safely through, and the feedback was good enough to help me make a decision without second-guessing."

### **4.3. Performance in Varying Environments**

The performance of the system was further tested in various environmental conditions:

- Indoor Environments: A space as controlled as a hallway or even a room, with static objects around, saw the system achieve almost perfect detection of obstacles with an accuracy of 96.8%. For detailed mapping close-range obstacles like walls and furniture, LIDAR sensors were very effective along with ultrasonic sensors, but navigating with haptic feedback provided by the device ensured smooth navigation.
- Outdoor **Environments:** In dynamic outdoor environments, added complexity from moving obstacles like pedestrians and vehicles led to a slight accuracy decrease to 92.1%, but users could still avoid most obstacles effectively with real-time feedback, while sensor data fusion ensured that all critical information reached the user in time. To a slight accuracy decrease to 92.1%, but users could still avoid most obstacles effectively with real-time feedback, while sensor data fusion ensured that all critical information reached the user in time, shown in Figure 3.

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Figure 3 Soncer Data Fusion	

**Figure 3** Sensor Data Fusion

### 5. Conclusion and Summary of Results

Experiment results of the proposed system combined with haptic feedback, which clearly shows improvement in obstacle avoidance capability among the visually impaired users. The accuracy of both obstacle detection and navigation by the proposed system is really good and the haptic feedback that provides spatial information to the user in an intuitive and reliable manner.

- **Overall Detection Accuracy:** 94.2%
- **Obstacle Avoidance Rate:** 92.8%
- User Satisfaction: High
- Error Rate: 7.2%

### Conclusion

we've introduced an advanced obstacle detection and navigation system for visually impaired individuals that combines deep learning with multi-sensor technologies, including cameras, ultrasonic sensors, and LIDAR. By integrating these technologies, the system offers reliable, real-time detection and classification of obstacles. Haptic feedback devices enable users to receive immediate, intuitive cues about their surroundings, enhancing navigation even in complex environments. Our results indicate that this system not only matches conventional mobility aids in accuracy and speed but also offers enriched spatial awareness through adaptive tactile feedback. This enables users to make faster decisions with less cognitive load compared to auditory-based feedback, which can be confusing or overwhelming. Overall, this research represents a meaningful step forward in assistive technology, using AI and multi-modal sensors to improve mobility and quality of life for individuals with visual impairments. As this technology evolves, we envision a world where everyone has the freedom to navigate safely and confidently.

### References

- [1]. Chucai Yi et al. "Finding objects for assisting blind people". In: Network Modeling Analysis in Health Informatics and Bioinformatics 2.2 (2013), pp. 71–79.
- [2]. Menghan Hu et al. "An overview of assistive devices for blind and visually impaired people". In:Interna-tional Journal of Robotics and Automation 34.5 (2019),



pp. 580–598.

- [3]. lessandro Dionisi, Emilio Sardini, and Mauro Serpel-loni. "Wearable object detection system for the blind". In:2012 IEEE International Instrumentation and Measure-ment Technology Conference Proceedings. IEEE. 2012,pp. 1255–1258.
- [4]. Ferdousi Rahman, Israt Jahan Ritun, and Nafisa Farhin. "Assisting the visually impaired people using image processing". PhD thesis. BRAC University, 2018.
- [5]. Jinqiang Bai et al. "Smart guiding glasses for visually impaired people in indoor environment". In: IEEE Transactions on Consumer Electronics 63.3 (2017), pp. 258–266.
- [6]. Hanen Jabnoun, Faouzi Benzarti, and Hamid Amiri. "Object detection and identification for blind people in video scene". In: 2015 15th International Conference on Intelligent Systems Design and Applications (ISDA). IEEE. 2015, pp. 363–367.
- [7]. Hanen Jabnoun, Faouzi Benzarti, and Hamid Amiri. "Object detection and identification for blind people in video scene". In: 2015 15th International Conference on Intelligent Systems Design and Applications (ISDA). IEEE. 2015, pp. 363–367.
- [8]. Shaoqing Ren et al. "Faster R-CNN: Towards Real-Time Object Detec- tion with Region Proposal Networks". In: realtime-object- detection-with-regionproposal-networks.
- [9]. hristian Szegedy, Alexander Toshev, and Dumitru Er-han. "Deep neural networks for object detection". In:Ad-vances in neural information processing systems. 2013, pp. 2553–2561.
- [10]. Jun Zhu, Xianjie Chen, and Alan L Yuille. "DeePM: A deep part- based model for object detection and semantic part localization". In: arXiv preprint arXiv:1511.07131 (2015).