West Science Information System and Technology
Vol. 3, No. 03, December 2025, pp. 166~175

Designing an Object Detection System as an Assistive Device for the Visually Impaired Based on Yolo V10 with Dual Camera

Amalia Nabila[1], Farida Arinie Soelistianto[2], Isa Mahfudi[3]
[1,2,3] Politeknik Negeri Malang

Article Info

Article history:

Received December, 2025
Revised December, 2025
Accepted December, 2025

Keywords:

Audio Output
Dual Camera
Object Detection
Visually Impaired
YOLOv10

ABSTRACT

This research develops an object detection system to assist visually impaired individuals in navigating dynamic environments, including roads and indoor spaces. The system employs YOLO version 10 (YOLOv10) with dual cameras and provides audio output through a speaker. Using the Research and Development (R&D) method, the system detects six object classes—person, car, motorcycle, bicycle, table, and chair—in real-time. Testing was conducted with variations in distance, lighting conditions, delay, and direct trials with visually impaired users. Results show an effective detection range of up to 5 meters. Under bright indoor lighting, the average error was 8.97%, while outdoor morning conditions yielded 3.95%. In low-light and dark conditions, accuracy decreased significantly, with errors ranging from 60.33% to 100%. Detection delay ranged from 4.3 to 7.4 seconds. The system achieved a Macro F1-Score of 0.74, with the highest performance for cars (0.92) and the lowest for persons (0.62). Direct trials with five visually impaired participants showed an average accuracy of 92.58% and delays around 4.63 seconds. The system effectively delivers precise audio information, helping users recognize objects in front and behind, thereby enhancing safety and confidence during navigation.

Corresponding Author:

Name: Amalia Nabila
Institution: Politeknik Negeri Malang
Email: amalianabila2803@gmail.com

1. INTRODUCTION

The rapid advancement of artificial intelligence (AI) and computer vision has created new opportunities to develop assistive technologies for people with disabilities. Among them, object detection systems have emerged as essential solutions to enhance safety and independence for individuals with visual impairments. By leveraging deep learning algorithms, these systems can provide real-time information about the surrounding environment, enabling users to navigate more confidently and securely in dynamic situations. This technological innovation plays a crucial role in improving accessibility and inclusivity in society, particularly for the visually impaired, who often face significant mobility challenges in their daily lives [1].

In Indonesia, the number of people with visual impairments reaches approximately 1.5% of the total population, equivalent to more than four million individuals [2]. Limitations in vision affect various aspects of their daily activities, such as recognizing objects, avoiding obstacles, or crossing streets safely. Traditional assistive devices, such as canes or guide dogs, provide limited support and often fail to deliver sufficient information about the spatial characteristics of objects in complex environments [3]. Therefore, innovative approaches are required to address these challenges by integrating advanced sensing and processing technologies into wearable assistive systems [4].

Previous studies have implemented object detection methods such as Connected Component Labeling and YOLOv4-Tiny to assist visually impaired individuals [6][7]. While these systems demonstrated promising results, they were constrained by limited accuracy, single-camera input, and insufficient adaptability to dynamic lighting and outdoor conditions. The lack of depth perception and spatial awareness also reduced their effectiveness in real-world scenarios, where accurate detection of object type, position, and distance is essential for user safety [8].

To overcome these limitations, this study introduces the design of an object detection system based on YOLOv10 integrated with dual cameras. YOLOv10 was chosen due to its high accuracy and ability to perform real-time object detection, while the dual-camera setup enhances spatial perception and allows detection from both the front and rear directions. The system provides audio output through a speaker, delivering real-time object recognition results directly to users. By focusing on six classes of objects—people, cars, motorcycles, bicycles, tables, and chairs—the system is expected to support visually impaired individuals in navigating both indoor and outdoor environments more effectively [9].

The implementation of YOLOv10 in this system is carried out using Raspberry Pi as the main processor, ensuring portability and efficiency. The research compares the performance of YOLOv10 with YOLOv4 as a benchmark, analyzing detection accuracy, delay, and robustness under various environmental conditions. Furthermore, testing is conducted not only in controlled laboratory scenarios but also through direct trials with visually impaired respondents to evaluate usability and effectiveness in real-life situations [10].

This study contributes to the development of modern assistive devices that combine deep learning and embedded systems to improve accessibility for the visually impaired. The integration of dual-camera object detection and audio feedback is expected to increase user independence, safety, and confidence during navigation. Moreover, the comparison of detection performance between YOLOv10 and earlier versions provides valuable insights for future improvements in computer vision–based assistive technologies.

2. LITERATURE REVIEW

2.1 Object Detection

Object detection is a computer vision technique used to identify and localize objects within digital images or video frames. Unlike simple image classification, which only determines the presence of an object, object detection provides spatial information by drawing bounding boxes around detected objects. This capability is particularly important in assistive technology for visually impaired individuals, where accurate identification and localization of surrounding objects directly contribute to safe navigation [11].

2.2 You Only Look Once (YOLO)

YOLO (You Only Look Once) is a deep learning–based object detection algorithm designed to achieve fast and accurate detection in a single processing step. Unlike region-based methods that generate candidate regions before classification, YOLO divides an image into grids and directly predicts bounding boxes and class probabilities for each grid cell. This approach significantly reduces computation time while maintaining high accuracy [12]. Over the years, YOLO has undergone several improvements, from YOLOv1 to the latest versions. YOLOv4 introduced performance optimizations for training on limited hardware, while YOLOv5 emphasized implementation flexibility with PyTorch. YOLOv7 and YOLOv8 further enhanced detection accuracy and multi-scale object recognition. The most recent version, YOLOv10, offers improvements in inference speed, energy efficiency, and robustness in complex environments. These advantages make YOLOv10 particularly relevant for real-time assistive applications such as wearable navigation devices for visually impaired users [13][14].

2.3 Dual Camera Systems

Dual camera systems are increasingly adopted in computer vision applications to enhance spatial perception and improve detection reliability. By combining two camera inputs, systems can capture images from different angles or directions, enabling better object tracking and depth estimation. For visually impaired assistive tools, dual cameras provide a wider field of view, reducing blind spots and increasing safety during navigation [15].

The integration of dual cameras with deep learning–based detection ensures that objects appearing both in the front and rear can be identified in real-time. This approach not only improves recognition accuracy but also supports multimodal outputs, such as audio feedback, that help users receive more comprehensive environmental information [16].

2.4 Raspberry Pi in Computer Vision Applications

Raspberry Pi is a compact, low-cost, and versatile microcontroller widely used in embedded system development, including computer vision applications. Equipped with sufficient processing power to run lightweight deep learning models, Raspberry Pi enables the deployment of portable object detection systems. Combined with cameras and external modules such as speakers, it can provide real-time assistive functionality without relying on high-performance servers [17].

The integration of Raspberry Pi with YOLO-based object detection models has been demonstrated in several studies, showing that it is capable of balancing performance, portability, and cost-effectiveness. This makes it a strong candidate for developing assistive technologies aimed at supporting the independence of visually impaired individuals [18].

3. METHODS

This research is categorized as Research and Development (R&D), focusing on the design and implementation of an object detection system as an assistive tool for visually impaired individuals. The system integrates several hardware and software components to enable real-time detection and audio feedback.

The hardware of the system was built using a Raspberry Pi 4 as the central processing unit. This device was chosen because of its portability and sufficient computational power to execute lightweight deep learning models. Two camera modules were employed as input devices, positioned at the front and rear to create a dual camera system. This configuration allows the device to capture a wider field of view, thereby increasing spatial awareness for the user. A mini speaker was added to deliver real-time audio feedback about detected objects, while the power supply module was equipped with voltage regulation to ensure the stable performance of all hardware components. The entire hardware configuration was designed to be compact and wearable, making it suitable for everyday use by visually impaired individuals.

The software component was implemented using the YOLOv10 object detection algorithm, selected for its high accuracy and real-time processing capabilities. The system was programmed in Python and executed on the Raspberry Pi platform. YOLOv10 was trained to recognize six object classes: person, car, motorcycle, bicycle, table, and chair. These classes were chosen because they represent common obstacles in both indoor and outdoor environments. To provide comparative evaluation, the YOLOv4 algorithm was also integrated as a benchmark model. Once the objects were detected, the results were processed and transmitted to the audio output system, enabling users to receive direct spoken feedback about their surroundings.

The overall system workflow begins with image capture from the dual cameras. The video frames obtained are processed by the YOLOv10 detection model, which identifies and classifies the objects present in the scene. The detection results are then processed by the Raspberry Pi to determine the type and position of the objects. Subsequently, the system translates this information into audio output that is delivered through the speaker. This process enables visually impaired users to receive real-time awareness of objects in their environment, both in front and behind them, thus improving navigation safety and independence.

Data collection was conducted through direct implementation of the system in both controlled and real-world environments. In controlled testing, objects were placed at different distances and angles indoors to measure the accuracy and detection delay of the system. In outdoor testing, the system was used by visually impaired respondents to evaluate performance under real navigation conditions. During both scenarios, object detection results, accuracy rates, false detection cases, and delay times were recorded for further analysis.

The data collected from system testing was analyzed quantitatively. Performance parameters such as detection accuracy, false positive rate, false negative rate, and processing delay were compared between YOLOv10 and YOLOv4. This comparison highlighted the improvements achieved by YOLOv10 in terms of accuracy and robustness in complex environments. Additionally, qualitative feedback from visually impaired respondents was taken into account to assess the practicality, usability, and comfort of the system in supporting independent navigation.

4. RESULTS AND DISCUSSION

4.1 YOLOv10 Object Detection Results

Based on Table 1, the YOLOv10 model was tested to evaluate its ability to detect six object categories, namely person, car, motorcycle, bicycle, chair, and table, under bright lighting conditions at a distance of 5 meters (both indoor and outdoor). The detection performance was assessed using confidence scores for each object class.

The recognition results showed that the YOLOv10 model achieved the highest accuracy in detecting the bicycle, with a confidence score of 95%, indicating strong reliability in identifying this class. The motorcycle (94%), person (93%), and car (92%) categories also demonstrated high accuracy levels, proving the robustness of the model in real-world scenarios. The chair category achieved a moderate accuracy with 86%, while the table recorded the lowest score at 57%, suggesting detection challenges for this object class.

Table 1. YOLOv10 Object Detection Results

No	Object	Detection Result	Confidence Score (%)
1	Person	Detected	93
2	Car	Detected	92
3	Motorcycle	Detected	94
4	Bicycle	Detected	95
5	Chair	Detected	86
6	Table	Detected	57

From the test results shown in Table 1, it is evident that YOLOv10 delivers varying performance depending on the object category. Objects with simpler shapes and stronger contrast against the background, such as bicycles and motorcycles, tend to achieve higher confidence scores. On the other hand, objects with complex structures or lower contrast, such as tables, produce lower detection accuracy.

4.2 Results of Distance Change Testing

The distance change testing was conducted both indoors and outdoors using the front and rear cameras under bright lighting conditions with distances ranging from 1 to 10 meters. Based on the results, several key findings can be highlighted:

4.2.1 Indoor Testing (Front Camera)

The front camera indoors showed relatively stable performance at distances up to 6 meters, with error values consistently below 10%. Accuracy began to degrade at longer ranges, particularly at 9–10 meters, where errors increased up to 22% depending on the object type.

4.2.2 Indoor Testing (Rear Camera)

Similar to the front camera, the rear camera indoors maintained good accuracy at short-to-medium ranges (1–6 meters) with error rates between 2–10%. However, at longer distances (7–10 meters), errors became more significant, especially for objects with complex shapes such as chairs, where errors exceeded 30%.

4.2.3 Outdoor Testing (Front Camera)

The outdoor front camera produced accurate readings at 1–5 meters with error values below 10%. However, performance dropped significantly beyond 6 meters, where errors ranged from 15–50%, especially for motorcycles and bicycles. Environmental factors such as sunlight, shadows, and background objects strongly influenced accuracy.

4.2.4 Outdoor Testing (Rear Camera)

The outdoor rear camera exhibited the highest variability. While performance was still acceptable at close ranges (1–3 meters), errors increased rapidly at longer distances, reaching 20–35% for motorcycles and bicycles. This indicates the rear camera is more sensitive to environmental interference and object positioning.

4.3 Test Results Effect of Light Intensity

The effect of light intensity was tested at an effective distance of 5 meters under various conditions both indoors (very bright, bright, dim, dark, very dark) and outdoors (morning, noon, afternoon, night) using the front and rear cameras.

4.3.1 Indoor Testing (Front Camera)

The front camera indoors performed well under very bright and bright conditions, with errors ranging from 1.2–10%. However, accuracy decreased significantly in dim and dark lighting, where errors reached 36–68%. In very dark conditions, detection failed entirely, resulting in 100% error.

4.3.2 Indoor Testing (Rear Camera)

The rear camera showed similar characteristics, maintaining acceptable accuracy under very bright and bright lighting with errors below 15%. Performance dropped under dim and dark conditions, with errors rising to 42–70%, and detection also failed in very dark conditions (100% error).

4.3.3 Outdoor Testing (Front Camera)

The outdoor front camera achieved excellent accuracy in daylight conditions (morning, noon, afternoon), with errors between 0–11%. However, during night testing, accuracy dropped sharply across all objects, producing errors up to 50–88%.

4.3.4 Outdoor Testing (Rear Camera)

The outdoor rear camera followed the same trend, where accuracy remained stable during daytime (errors between 2–11%) but dropped drastically at night, with errors exceeding 80%, especially for moving objects such as motorcycles and bicycles.

4.4 Test Results of the Effect When Users Take One Step

The effect of user movement was tested by simulating a single walking step at the effective distance of 5 meters, both indoors and outdoors, using the front and rear cameras. The goal was to observe how minor user movement impacts object distance detection.

4.4.1 Indoor Testing (Front Camera)

The front camera indoors showed small deviations when the user moved one step. Error values ranged between 4–13%, with the chair having the lowest error (4%) and the table the highest (13%). This indicates that the system can still maintain acceptable accuracy despite user movement.

4.4.2 Indoor Testing (Rear Camera)

The rear camera indoors produced slightly higher variations, with error rates between 4–12%. The table was detected most accurately (4% error), while the chair produced the highest error (12%). These results suggest that the rear camera is somewhat less stable than the front camera in compensating for user movement.

4.4.3 Outdoor Testing (Front Camera)

The outdoor front camera demonstrated very high accuracy across all objects, with error values consistently below 5%. The human object was detected perfectly (0% error), while vehicles such as motorcycles, cars, and bicycles showed minimal deviations (2.8–4.2% error). This highlights the robustness of the front camera outdoors under normal lighting conditions.

4.4.4 Outdoor Testing (Rear Camera)

The outdoor rear camera also achieved low error values, ranging from 1.4–6%. Among the tested objects, motorcycles were detected with the highest accuracy (1.4% error), while bicycles produced the largest deviation (6% error). Despite this, the overall performance remained highly reliable.

4.5 Delay Parameter Test Results

The delay parameter testing was conducted to evaluate the system's response time in detecting and announcing objects through audio output. The tests involved sequential detection of two different objects, both indoors and outdoors, using the front and rear cameras. The delay was measured as the time difference between the object's appearance in the camera frame and the audio response generated by the system.

4.5.1 Indoor Testing (Front Camera)

The front camera indoors showed delays ranging from 3 to 6 seconds. The fastest response occurred when detecting a chair–table sequence (3–4 seconds), while the slowest was during table–chair transitions (6 seconds). Overall, the system responded consistently but exhibited minor variations depending on the object pair being detected.

4.5.2 Indoor Testing (Rear Camera)

The rear camera indoors produced slightly longer delays, varying between 3 and 7 seconds. The fastest detection occurred in the table–chair sequence (3–5 seconds), while the slowest was table–chair and person–table transitions (7 seconds). This indicates that the rear camera requires slightly more processing time compared to the front camera in indoor environments.

4.5.3 Outdoor Testing (Front Camera)

The outdoor front camera recorded delays ranging from 3 to 9 seconds. The fastest response occurred in the bicycle–person sequence (3 seconds), while the longest delay was observed in the car–motorcycle sequence (9 seconds). Variability was higher outdoors due to environmental factors such as lighting and object movement.

4.5.4 Outdoor Testing (Rear Camera)

The rear camera outdoors produced delays of 4 to 10 seconds, making it the slowest among all conditions. The shortest delay was in the bicycle–person sequence (4–5 seconds), while the longest was in person–car transitions (10 seconds). These findings suggest that outdoor conditions significantly affect system performance, particularly with the rear camera.

4.6 Latency Test Results

Latency and frame rate testing were carried out to evaluate the system's performance in terms of processing speed and response time. The experiments were conducted at an effective distance of 5 meters under bright lighting conditions, using six different objects (person, table, chair, motorcycle, car, and bicycle) with both front and rear cameras, indoors and outdoors.

The latency testing showed that the front camera achieved better performance compared to the rear camera. On the front camera, the average latency ranged from 3900 ms for the chair to 5480 ms for the car. The fastest response was recorded for the chair (3900 ms / 130.0 ms per frame), while the car exhibited the highest latency (5480 ms / 182.7 ms per frame). These results indicate that simpler objects such as people and chairs were detected faster, whereas larger or more complex objects, including cars and motorcycles, required longer detection times.

On the other hand, the rear camera showed higher latency values, ranging from 4500 ms for the chair to 6070 ms for the car. Similar to the front camera, the chair was detected the fastest (4500 ms / 150.0 ms per frame), while the car had the slowest response (6070 ms / 202.3 ms per frame). Overall, the rear camera consistently exhibited longer latency compared to the front camera, suggesting higher processing overhead or reduced efficiency in object recognition.

4.7 Model Evaluation Test Results

Model evaluation was conducted to assess the performance of YOLOv10 in waste classification using key metrics such as Precision, Recall, F1-Score, and Mean Average Precision (mAP). The training process was carried out with an image size of 640, 100 epochs, and a batch size of 16. Figure 4.9 presents the confusion matrix, which illustrates the model's ability to predict each class during training and provides a clear overview of classification accuracy for all categories.

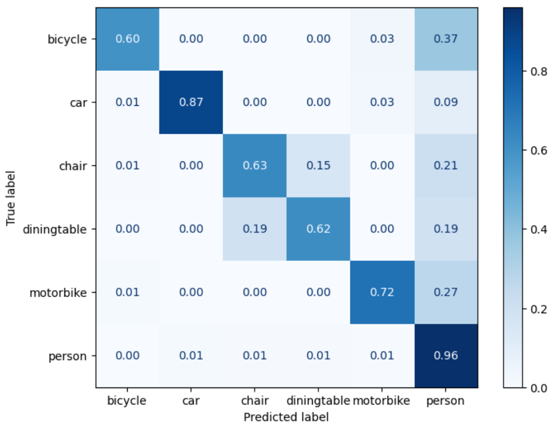

Figure 1. *Confusion Matrix*

The evaluation of the YOLOv10 model demonstrated varying performance different object classes, as reflected in the metrics of Accuracy, Precision, Recall, and F1-Score.

Table 2. System Performance

Class	Accuracy	Precision	Recall	F1-Score
Table	91%	0.79	0.62	0.69
Chair	90.5%	0.759	0.63	0.68
Person	80.5%	0.459	0.96	0.62
Car	97.6%	0.988	0.87	0.92
Motor	94.2%	0.911	0.72	0.80
Bicycle	92.83%	0.952	0.60	0.73

For the bike class, the model achieved good accuracy (92.83%) and very high precision (0.952), showing most predicted bikes were correct. However, recall was only 0.60, meaning 40% of actual bikes were missed, indicating the model prioritizes precision over sensitivity.

For the car class, performance was the best overall, with 97.6% accuracy, 0.988 precision, and 0.87 recall (F1-Score 0.92). This shows consistent and reliable detection with minimal errors. The chair and table classes showed moderate performance, with accuracies around 90–91%, precision near 0.76–0.79, and recall around 0.62–0.63. The relatively low recall indicates the model struggles with detecting these objects, likely due to visual complexity and similarity with other furniture.

For the motorcycle class, results were strong, with 94.2% accuracy, 0.911 precision, and 0.72 recall (F1-Score 0.80). The system detects motorcycles well but still misses nearly 30% of them. The person class had the weakest balance. Recall was very high (0.96), but precision was very low (0.459), leading to frequent false positives and the lowest F1-Score (0.62). This suggests difficulty distinguishing people from other objects.

At the overall level, the model reached precision and recall of 0.733 each, with a Macro F1-Score of 0.74. It performs best on structured objects (cars, motorcycles) but struggles with variable or complex shapes (people, chairs, tables).

4.8 Results of Device Testing on Users

Table 3. Average Performance Results on Respondents

Respondent	Avg Distance	Avg Accuracy	Avg Delay
Respondent 1	4.76 m	95.13%	3.62 s
Respondent 2	4.66 m	93.15%	4.06 s
Respondent 3	4.64 m	92.72%	3.34 s
Respondent 4	4.64 m	87.14%	3.59 s
Respondent 5	4.57 m	91.16%	3.81 s
Average	4.65 m	91.86%	3.68 s

Device testing with blind users demonstrated strong overall performance, achieving an average accuracy of 91.86%, a detection distance of 4.65 meters, and a delay of 3.68 seconds. In indoor trials, the front camera showed excellent results in detecting people, reaching up to 100% accuracy, while the rear camera offered more balanced performance, particularly for tables with an accuracy of 87.4% compared to 83.64% on the front camera. Outdoor testing also showed high accuracy, with human detection consistently above 97% and vehicles above 94%, although bicycle detection remained weaker at around 85–90% with higher delays. Between the two cameras, the rear camera delivered more consistent results outdoors. Across respondents, slight variations were observed, with Respondent 1 achieving the highest accuracy of 95.13%, Respondent 3 recording the fastest delay of 3.34 seconds, and Respondent 4 showing the lowest accuracy at 87.14%. User feedback highlighted the system's effectiveness, especially the audio output that supported navigation, but also pointed out issues with device weight and volume levels indoors. Overall, the system proved effective in assisting navigation, combining reliable detection with acceptable delay, while further improvements are needed in reducing device weight and integrating adaptive audio features for enhanced usability.

5. CONCLUSION

The development of an object detection system based on YOLOv10 with dual cameras as an assistive tool for the visually impaired was successfully implemented and tested. Distance testing showed that 5 meters was the most effective range, with a low error rate across conditions (front camera indoor 2.4%, outdoor 5.3%; rear camera indoor 3.4%, outdoor 4.9%). Light intensity had a significant effect on performance, where indoor accuracy was highest under very bright conditions (1037 lux, error rate 8.97%), but degraded drastically in dark environments, reaching 100% error at 0 lux. Outdoor testing achieved the best results in the morning (6695 lux, error rate 3.95%), while at night (9 lux), error rates increased up to 69.15%.

Latency analysis revealed delays ranging from 4.3 to 6.8 seconds, with the front camera performing faster (4703 ms) compared to the rear camera (5258 ms). Object-wise, the lowest latency was achieved for chairs (13.3%) and people (12.6%). Frame rate measurements showed the front camera achieved 156.7 ms/frame, while the rear camera reached 175.3 ms/frame.

In terms of object recognition, YOLOv10 achieved a true positive rate (TPR) of 96% for people, indicating strong performance in human detection. Vehicles such as cars and motorcycles showed balanced results with TPRs of 87% and 72%, while bicycles performed weaker at 60%. Chairs and tables also showed moderate results at 63% and 62%. The model achieved a Macro F1-Score of 0.74 (74%), with overall precision and recall of 73.3%, indicating solid overall performance. Accuracy analysis showed the highest accuracy for cars (97.6%), followed by motorcycles (94.2%), bicycles (92.83%), chairs (90.5%), and people (80.5%).

Finally, user testing with five blind respondents demonstrated strong real-world performance, achieving an average accuracy of 91.86%, an average detection distance of 4.65 meters, and an average delay of 3.68 seconds. These results confirm that the YOLOv10-based dual camera system is effective in assisting navigation for visually impaired users, while further improvements are recommended through dataset expansion and the inclusion of additional obstacle types

REFERENCES

[1] F. H. Gunawan, A. B. Laksono, and A. Bachri, “Rancang bangun alat bantu bagi penyandang tunanetra,” Semin. Nas. Fortei Reg. 7, pp. 35–40, 2020.

[2] R. R. N. Sulistyowati, “Sistem Pakar untuk Mendiagnosis Penyakit Mata Berbasis Web dengan Menggunakan Metode Forward Chaining,” SNESTIK Semin. Nas. Tek. Elektro, Sist. Inf. dan Tek. Inform., pp. 219–224, 2021.

[3] M. Aulia, E. Prihatini, and N. L. Husni, “Perancangan Kendali Alat Bantu Tunanetra Berbasis Fuzzy Logic,” J. Rekayasa Elektro Sriwij., vol. 1, no. 2, pp. 62–70, 2020, doi: se 10.36706/jres.v1i2.15.

[4] J. Kuswanto, “Implementasi (GaBlind) Alat Bantu Navigasi Tunanetra Menggunakan Sensor Max Sonar Berbasis Arduino,” Intechno J. Inf. Technol., vol. 1, no. 4, pp. 19–23, 2019.

[5] D. Aryani, A. I. Gunawan, R. Reski, K. Nisa, and A. Zubair, “Alat Bantu Jalan Tunanetra Menggunakan Sensor Light Detection and Ranging (LiDAR) Berbasis Arduino,” J. Teknol. Elekterika, vol. 20, no. 2, p. 98, 2023, doi: 10.31963/elekterika.v20i2.4587.

[6] R. Syahputra, A. Yusupa, and B. J. Sitompul, “Topi Peringatan Bahaya Penyandang Tunanetra Berbasis Mikrokontroller dengan Sensor Ultrasonik Menggunakan Metode Research and Development,” J. SAINTIKOM, vol. 23, no. 1, p. 221, 2024, doi: 10.53513/jis.v23i1.9591.

[7] I. Yusnilawati, F. Utaminingrum, and M. H. H. Ichsan, “Implementasi Connected Component Labeling untuk Deteksi Objek Penghalang Bagi Penyandang Tunanetra Berbasis Raspberry Pi,” J. Pengemb. Teknol. Inf. dan Ilmu Komput., vol. 3, no. 2, pp. 1318–1323, 2019. [Online]. Available: http://repository.ub.ac.id/14111/

[8] Y. An and H. S. Kim, “A systematic review of computer vision technology applied for individuals with disabilities,” J. Digit. Media Cult. Technol., vol. 3, no. 2, pp. 67–87, 2023, doi: 10.29056/jdmct.2023.12.01.

[9] . M. Yusup, A. F. Anugrah, D. D. Muslimah, S. M. W. N. Permana, and S. Yuliani, “Pendeteksian Objek Menggunakan OpenCV dan Metode YOLOv4-TINY untuk Membantu Tunanetra,” J. Comput. Sci. Inf. Technol., vol. 1, no. 2, pp. 59–68, 2024, doi: 10.59407/jcsit.v1i2.532.

[10] F. Indaryanto, A. Nugroho, and A. F. Suni, “Aplikasi Penghitung Jarak dan Jumlah Orang Berbasis YOLO Sebagai Protokol Kesehatan Covid-19,” Edu Komputika J., vol. 8, no. 1, pp. 31–38, 2021, doi: 10.15294/edukomputika.v8i1.47837.

[11] S. Fuady, N. Nehru, and G. Anggraeni, “Deteksi Objek Menggunakan Metode Single Shot Multibox Detector pada Alat Bantu Tongkat Tunanetra Berbasis Kamera,” J. Electr. Power Control Autom., vol. 3, no. 2, p. 39, 2020, doi: 10.33087/jepca.v3i2.38.

[12] J. Ilm. Komputasi, “Pembuatan Aplikasi Deteksi Objek Menggunakan TensorFlow Object Detection API dengan Memanfaatkan SSD MobileNet V2 Sebagai Model Pra-Terlatih,” J. Ilm. Komputasi, vol. 19, no. 3, pp. 421–430, 2020, doi: 10.32409/jikstik.19.3.68.

[13] A. Praptaningrum, “Penerapan Bahan Ajar Audio untuk Anak Tunanetra Tingkat SMP di Indonesia,” vol. 5, pp. 1–19, 2020.

[14] K. Rani, A. Rafikayati, and M. N. Jauhari, “Keterlibatan Orangtua dalam Penanganan Anak Berkebutuhan Khusus,” J. Abadimas Adi Buana, vol. 2, no. 1, pp. 55–64, 2018, doi: 10.36456/abadimas.v2.i1.a1636.

[15] J. Jumadi, Y. Yupianti, and D. Sartika, "Pengolahan Citra Digital untuk Identifikasi Objek Menggunakan Metode Hierarchical Agglomerative Clustering," JST (Jurnal Sains dan Teknol.), vol. 10, no. 2, pp. 148–156, 2021, doi: 10.23887/jstundiksha.v10i2.33636.

[16] R. F. Muharram and A. Suryadi, "Implementasi artificial intelligence untuk deteksi masker secara realtime dengan TensorFlow dan SSD MobileNet berbasis Python," Jurnal Widya, vol. 3, pp. 281–290, 2022.

[17] A. N. Sugandi and B. Hartono, "Implementasi Pengolahan Citra pada Quadcopter untuk Deteksi Manusia Menggunakan Algoritma YOLO," Pros. 13th Ind. Res. Work. Natl. Semin., pp. 13–14, 2022.

[18] S. K. Bhandary, R. Dhakal, V. Sanghavi, and P. K. Verkicharlai, "Ambient light level varies with different locations and environmental conditions: Potential to impact myopia," PLoS One, vol. 16, no. 7, pp. 1–13, 2021.