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Development of an AI-based object detection tool for the visually impaired using Raspberry Pi and a camera. Case study: Griya Harapan Social Service Center for the Disabled, Cimahi, Jawa Barat

Achmad Lukman [a), Aaz Muhammad Hafidz Azis [b), I Wayan Palton Anuwiksa [c)

School of Computing, Telkom University, Bandung, Indonesia

[a)Corresponding author: alukman@telkomuniversity.ac.id
[b)aazmuhammad@telkomuniversity.ac.id
[c)paltonanuwiksa@telkomuniversity.ac.id

ABSTRACT

The limitation of identifying Objects in the surrounding environment is a major problem for blind people, especially those with low vision (who cannot see at all), which impacts their independence and participation in socio-economic life. To address this problem, the Community Service Team of the Faculty of Informatics at Telkom University conducted community service activities funded by Diktisaintek to develop and implement an AI-based visual aid for the blind. This aid utilizes a Raspberry Pi, camera, and headset that can recognize approximately 80 objects. The implementation method includes observation at the Griya Harapan Difabel Social Service Center as a partner, technology design, socialization and training on its use, field assistance, and evaluation. The evaluation model was carried out by implementing direct interviews with users to determine the objects that can be detected by the aid when using the device. The implementation results showed that the recognition accuracy level reached 80%. The social impacts achieved include increased independence for people who are blind, reduced risk of accidents, and new opportunities to participate in socio-economic activities. Obstacles encountered include limited datasets, variations in initial user skills, and the relatively high cost of the device. However, there are still ample opportunities for development, such as integration with mobile applications, improving CNN accuracy, and adding GPS features. This program demonstrates that technological innovation can be a sustainable solution to support the well-being and independence of people with disabilities.

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INTRODUCTION

Indonesia has a very large population of people with disabilities, with approximately 22.7 million people, of whom approximately 3.75 million are blind. This figure underscores the urgency of developing accessibility solutions that are not only safe and affordable but also easy to use in everyday life. The main challenges faced by the blind include mobility, object recognition, information access, and independence in activities (Hakobyan et al., 2013; Manjari et al., 2020; Elmannai & Elleithy, 2017; Beingolea et al., 2021; Kathiria et al., 2024).

Device-based assistive technology has advanced rapidly over the past decade. Features like TalkBack on Android and VoiceOver on iOS allow visually impaired people to access basic phone functions through voice and touch feedback. Additionally, apps like Be My Eyes and Seeing AI expand capabilities by offering remote visual assistance and automatic object or text recognition (Hakobyan et al., 2013; Naayini et al., 2025; Kathiria et al., 2024; Katke & Pacharaney, 2024). However, research shows that existing solutions still have limitations. Many commercial devices are expensive, poorly integrated, or have not been fully tested in real-world settings with visually impaired users in developing countries. In addition, technology adoption is often hampered by a lack of adequate training, socialization, and knowledge transfer to users and communities (Manjari et al., 2020; Elmannai & Elleithy, 2017; Beingolea et al., 2021; Balakrishnan, 2022; Manirajee et al., 2024).

Innovations based on computer vision and artificial intelligence (AI) offer significant potential to overcome these limitations. For example, devices based on a Raspberry Pi and a camera can be developed into multifunctional tools capable of real-time object detection, text reading, and navigation at a significantly lower cost than commercial solutions (Kral et al., 2025; Naayini et al., 2025; Beingolea et al., 2021; Katke & Pacharaney, 2024).

Recent research suggests that low-cost devices like these can increase user independence and confidence, especially when equipped with intuitive audio or haptic feedback. However, technical challenges such as processing speed, device miniaturization, and battery life still need to be optimized to make the devices truly practical for everyday use (Kral et al., 2025; Elmannai & Elleithy, 2017; Katke & Pacharaney, 2024; Zafar et al., 2022).

Beyond technical aspects, the successful implementation of assistive devices depends heavily on the transfer of knowledge to the user community. Training, mentoring, and ongoing support are crucial for users to maintain and adapt the devices to their needs. The involvement of local partners, such as social service centers, is key to ensuring the sustainability and relevance of the solution (Beingolea et al., 2021; Balakrishnan, 2022; Manirajee et al., 2024). Evaluation of the success of assistive devices is measured not only by technological accuracy but also by user convenience, ease of adoption, and impact on user independence. Studies emphasize the importance of a user-centered design approach to ensure that devices truly address real needs and achieve widespread acceptance (Manjari et al., 2020; Kathiria et al., 2024; Katke & Pacharaney, 2024; Madake et al., 2023).

On the other hand, the integration of AI technology and Visible Light Communication (VLC) is beginning to be explored to improve the reliability and flexibility of assistive devices, especially in object recognition and navigation in complex environments (Naayini et al., 2025; Lavric et al., 2024). Multidisciplinary collaboration between researchers, developers, and the blind community is essential to accelerate innovation and ensure that the resulting solutions are inclusive and sustainable (Hakobyan et al., 2013; Naayini et al., 2025; Zhang & Zhou, 2024; Kathiria et al., 2024).

Despite rapid technological advances, ethical, economic, and real-world adaptation challenges

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remain key concerns. Research highlights the need for field testing, adaptation to local contexts, and the development of business models that ensure assistive devices remain affordable for the wider population (Manjari et al., 2020; Elmannai & Elleithy, 2017; Beingolea et al., 2021; Zafar et al., 2022).

Thus, developing reliable, affordable, and easy-to-use assistive devices for the visually impaired require a holistic approach: combining technological innovation, training and mentoring, and social impact evaluation. This effort will not only improve the quality of life for visually impaired people but also promote greater social inclusion and independence in society (Hakobyan et al., 2013; Kral et al., 2025; Naayini et al., 2025; Beingolea et al., 2021; Kathiria et al., 2024; Katke & Pacharaney, 2024).

METHOD

The implementation method for this activity is designed systematically and participatory so that Raspberry Pi-based assistive devices for the visually impaired can be developed, tested, and optimally utilized by partners. Each stage refers to best practices in assistive technology development that emphasize user engagement, effectiveness, and desirability.

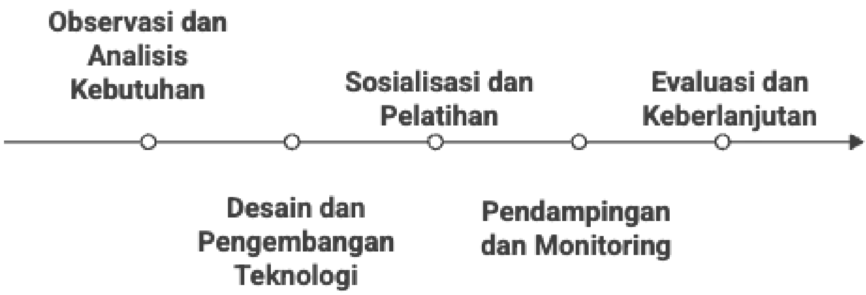

FIGURE 1. The Implementation Method

Needs Analysis

The initial stage involved direct observation and interviews within the partner's environment, the Griya Harapan Social Service Center for the Disabled in Cimahi. This was done to identify key issues, such as the limitations of conventional assistive devices, which only detect obstacles without recognizing objects or money. Analysis of the observations was used to formulate the need for relevant and contextual assistive devices.

Technology Design and Development

Based on the identified needs, a tool was designed using a Raspberry Pi, a webcam, and a Convolutional Neural Network (CNN) model for object detection. The design focused on being user-friendly, lightweight, and easy to use, integrating Python-based hardware and software to produce a testable prototype.

CNN Architecture

The CNN model architecture used in this study is mobilenetV2 with the network layer structure

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shown in Table 1.

TABLE 1. MobileNet architecture with input dimension 224x 224 x3

Input	Operator
224 x 224 x 3	Convolutional 2D
112 x 112 x 32 bottleneck	112 x 112 x 32 bottleneck
112 x 112 x 16 bottleneck	112 x 112 x 16 bottleneck
56 x 56 x 24 bottleneck	56 x 56 x 24 bottleneck
28 x 28 x 32 bottleneck	28 x 28 x 32 bottleneck
14 x 14 x 64 bottleneck	14 x 14 x 64 bottleneck
14 x 14 x 96 bottleneck	14 x 14 x 96 bottleneck
7 x 7 x 160 bottleneck	7 x 7 x 160 bottleneck
7 x 7 x 320 Convolution 2D 1 x 1	7 x 7 x 320 Convolution 2D 1 x 1
7 x 7 x 1280 Average Pooling 7 x 7	7 x 7 x 1280 Average Pooling 7 x 7
1 x 1 x 1280 Convolution 2D 1 x 1	1 x 1 x 1280 Convolution 2D 1 x 1

This architecture uses residual connections as shortcuts to facilitate fast learning capabilities in generalizing dataset learning and produces better accuracy (Sandler, et al 19).

Datasets

Research on the development of tools using the MS COCO dataset (Reddy, K. G., & Basha, 2025) for real-time object classification that provides 80 object categories along with bounding boxes and category labels involving 330,000 images. The categories used in this study have labels that are used only 50 categories, namely people, bicycles, cars, motorcycles, planes, buses, trains, trucks, boats, red lights, stop signs, benches, birds, cats, dogs, horses, sheep, cows, backpacks, umbrellas, handbags, ties, suitcases, balls, kites, tennis rackets, bottles, cups, forks, spoons, bowls, bananas, apples, oranges, cakes, chairs, carrots, sofa chairs, beds, dining tables, monitors, refrigerators, books, clocks, flower vases, scissors, toothpicks, sinks, cellphones.

Socialization and Training

Once the prototype was ready, intensive outreach and training was conducted for partners. The training included an introduction to the tool's functions, how to use it, and interpreting the sound output. Student mentoring was also provided to ensure effective knowledge transfer.

Mentoring and Monitoring

This stage includes monitoring device usage in daily activities, technical consultations, and documentation of user experiences. The mentoring aims to increase technology adoption and user confidence.

Evaluation and Sustainability

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Evaluations were conducted using questionnaires and direct observation to assess object detection accuracy. The results were used to improve the equipment. Sustainability strategies included transferring technical knowledge, establishing small teams within partner agencies, and engaging social services to support long-term maintenance and use.

RESULTS AND DISCUSSION

Observation

The observation phase was conducted at the Griya Harapan Social Service Center for the Disabled in Cimahi. Interviews with the administrators and visually impaired individuals revealed that the primary limitation was difficulty recognizing surrounding objects and currency denominations. The cane only detects physical obstacles without providing detailed information. This information served as the basis for designing an appropriate technology solution based on a Raspberry Pi and a camera.

FIGURE 2. Observation.

Technology Design

Based on observations, the community service team from Telkom University's Faculty of Informatics designed a device equipped with a mini chest camera and a Raspberry Pi as a processing center. This device utilizes an AI method, namely a Convolutional Neural Network (CNN), to recognize objects seen by the camera. The identification results are delivered via an audio headset, allowing users to immediately understand visual information about their surroundings.

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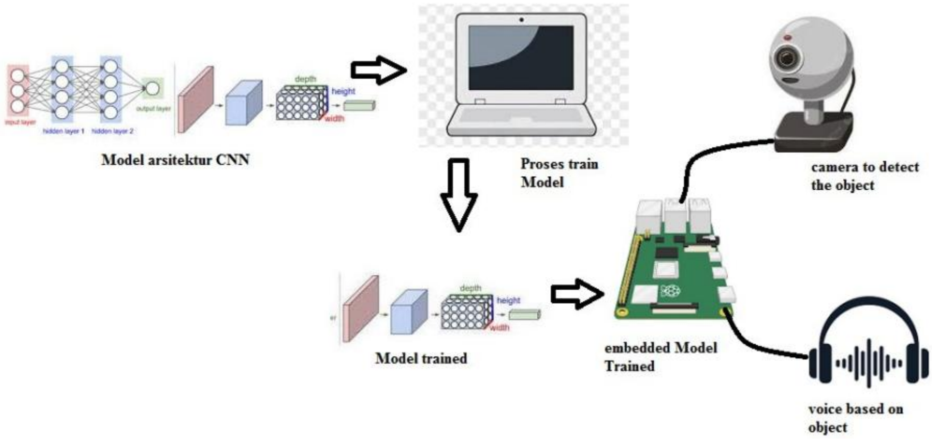

FIGURE 3. Design of the device

Figure 3 shows the design results for a Raspberry Pi-based visual aid device used in a public service room. A blind person stands in the center of the room, wearing a white shirt, with a small camera mounted on his chest and a headset connected to a device held in his hand. This device detects objects or monetary amounts and then transmits information in the form of sound to the user.

FIGURE 4. Implementation of Assistive Tools

Mentoring

Mentoring was conducted after the training to ensure the equipment could be used independently. Mentoring activities included monitoring equipment use, technical consultations, and regular documentation. Observations showed that most participants were becoming accustomed to using the equipment in their daily activities, although some still needed more time to adapt.

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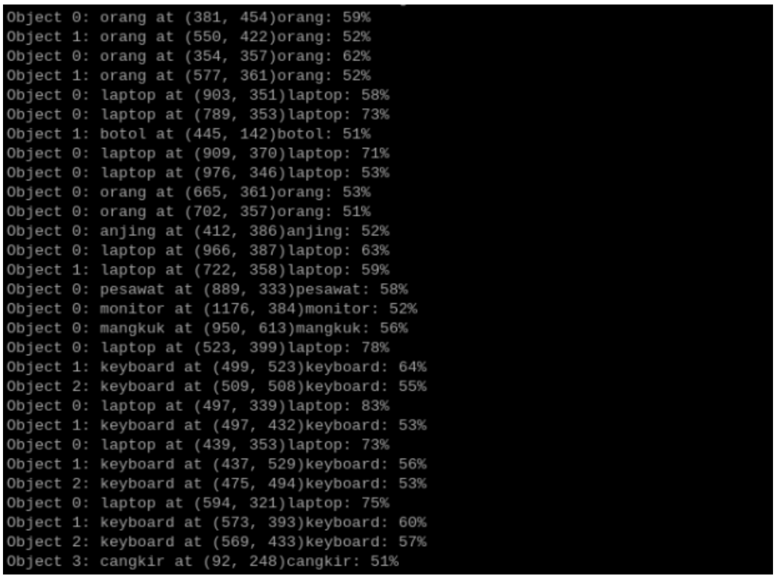
FIGURE 5. Technical assistance and monitoring of the equipment

Evaluation and Measurement

The evaluation was conducted using an object detection recording instrument from a device used by a blind student in a partner environment. In the initial stages, the student was unable to detect objects in front of him, unless the object made a sound, for example, a person's voice or footsteps, a television with audible sound, or by feeling with a stick or hand, and the like. However, this still allowed for collisions with objects in front of the blind student. Therefore, the effectiveness of the device's detection can be tested as shown in Table 2, obtained from monitoring using a laptop, an example of which is shown in Figure 6.



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Object 0: orang at (381, 454)orang: 59%
Object 1: orang at (550, 422)orang: 52%
Object 0: orang at (354, 357)orang: 62%
Object 1: orang at (577, 361)orang: 52%
Object 0: laptop at (903, 351)laptop: 58%
Object 0: laptop at (789, 353)laptop: 73%
Object 1: botol at (445, 142)botol: 51%
Object 0: laptop at (909, 370)laptop: 71%
Object 0: laptop at (976, 346)laptop: 53%
Object 0: orang at (665, 361)orang: 53%
Object 0: orang at (702, 357)orang: 51%
Object 0: anjing at (412, 386)anjing: 52%
Object 0: laptop at (966, 387)laptop: 63%
Object 1: laptop at (722, 358)laptop: 59%
Object 0: pesawat at (889, 333)pesawat: 58%
Object 0: monitor at (1176, 384)monitor: 52%
Object 0: mangkuk at (950, 613)mangkuk: 56%
Object 0: laptop at (523, 399)laptop: 78%
Object 1: keyboard at (499, 523)keyboard: 64%
Object 2: keyboard at (509, 508)keyboard: 55%
Object 0: laptop at (497, 339)laptop: 83%
Object 1: keyboard at (497, 432)keyboard: 53%
Object 0: laptop at (439, 353)laptop: 73%
Object 1: keyboard at (437, 529)keyboard: 56%
Object 2: keyboard at (475, 494)keyboard: 53%
Object 0: laptop at (594, 321)laptop: 75%
Object 1: keyboard at (573, 393)keyboard: 60%
Object 2: keyboard at (569, 433)keyboard: 57%
Object 3: cangkir at (92, 248)cangkir: 51%
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FIGURE 6. The result of object detection via laptop connection, as seen by the camera of the tool created.

Based on Figure 6, it shows an object detected by the camera and the name of the object is immediately displayed on the tool, which then with the help of a text to speech library sends a voice signal to the person using the tool.

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TABLE 2. Results of object detection trials using indoor tools

No	Objek	Object Detected?
1	Kursi	Yes
2	Orang	Yes
3	sepeda	No
4	meja makan	Yes
5	bangku	yes
6	kucing	Yes
7	tas ransel	No
8	payung	Yes
9	botol	Yes
10	sendok	Yes
11	pisang	Yes
12	kursi sofa	Yes
13	Monitor	Yes
14	Kulkas	No
15	gunting	Yes

Based on Table 2, it can be seen that the objects that were correctly recognized were 12/15 * 100 = 80, where 12 objects were the correct detection results while 15 was the number of categories involved in the room. After training and mentoring, the blind participants were enthusiastic about using the device, as the discussions revealed it could help them recognize objects in front of them. Thus, the target achievement indicator of 80% object detection accuracy by users was achieved

Based on the results of the activities and evaluations above, the sustainability of this community service program is designed through knowledge transfer to partners, both visually impaired people and the management of the Griya Harapan Social Service Center for the Disabled. Partners are provided with technical guidance on tool maintenance, including how to care for hardware such as cameras, batteries, and Raspberry Pi, as well as basic steps if the device experiences problems. With an internal team appointed by the partners, the use of the tool is expected to continue even though the PKM program has formally ended.

The sustainability program is also strengthened through collaboration with the West Java Provincial Social Services Agency. Regulatory support and guidance from the local government are expected to serve as a foundation for expanding the use of these assistive devices to other visually impaired groups. This way, the results achieved will not stop at the prototype stage but can be adopted as a long-term solution to support the independence of people with disabilities.

However, several obstacles were encountered during implementation that warrant further consideration. First, the limited dataset used to train the CNN model resulted in suboptimal accuracy in object and currency recognition. Second, varying user bases lead to varying adaptation processes, necessitating additional support for some participants. Third, the relatively high cost of the device presented challenges for mass production and widespread distribution.

On the other hand, there are still plenty of opportunities to develop this technology. One potential innovation is integration with mobile applications, allowing the device to connect to smartphones to expand functionality and accessibility. Furthermore, improving the accuracy of CNN models can be achieved through the collection of larger and more diverse datasets and the application of transfer

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learning methods. These steps will strengthen system performance while enhancing the user experience.

It is hoped that this assistive device will also have the potential to be developed into a more comprehensive device with the addition of GPS features. With real-time location navigation, this device will function not only as an object identifier but also as a mobility guide for people with visual disabilities. This innovation will expand the device's benefits beyond a technical solution to a social innovation product that supports the independence, safety, and long-term socio-economic participation of people with disabilities.

CONCLUSION

This community service activity successfully developed a Raspberry Pi-based visual aid for the blind equipped with a camera and headset to detect objects. The results of testing and evaluation through direct trials by blind partners showed a significant increase in identifying objects, reaching 80% accuracy, although there is a possibility of errors due to insufficient light intensity which can affect the results of object detection.

The positive impact of this program not only increases the independence of blind individuals in daily activities but also reduces the risk of accidents such as collisions and opens up new opportunities for socioeconomic participation. Furthermore, student involvement in every stage of the program contributes to the achievement of the university's Key Performance Indicators (KPIs), both in terms of off-campus learning experiences and scientific publications.

The program's sustainability is designed through knowledge transfer and technical assistance to partners, as well as collaboration with the West Java Provincial Social Services Office to ensure the continued use and development of the tool. Despite challenges such as limited data, varying skills among early adopters, and the relatively high cost of the device, the program continues to deliver tangible benefits to partners

There are still ample opportunities for technological development, including integration with mobile applications, improving the accuracy of CNN models using the MobileNet V2 architecture, and adding GPS features for navigation. With further innovation, this assistive device has the potential to become a social innovation product that supports broader and more sustainable independence, safety, and participation of people with disabilities.

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