Third Eye

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***Abstract*—This report details the development and implementation of an innovative assistive technology, coined as the "Third Eye" designed to aid visually impaired individuals in real-time navigation and object detection over long range. The system harnesses the power of two interconnected Raspberry Pi devices, with one functioning as the primary sensor unit equipped with a camera module and a LoRa (Long Range) module, and the other serving as the receiver. The sensor unit utilizes the camera to detect objects in the user's vicinity and, employing advanced image processing techniques, identifies these objects. Subsequently, the detected object labels are transmitted in real time via the integrated LoRa module to the second Raspberry Pi. This receiver unit, also equipped with a LoRa module, collects the transmitted data and processes it to provide accessible feedback to the user. This novel approach of combining real-time object detection with long-range, low-power communication technology showcases a significant step forward in assistive devices for the visually impaired. The "Third Eye" project not only enhances the autonomy and safety of its users but also demonstrates the potential of IoT and edge computing in creating impactful, user-centric solutions. The complete documentation and codebase for the "Third Eye" are available at [GitHub Link].**

***Index Terms*—Object Detection, Cost-effective, Large Area Network, Visual Impairment**

I. Introduction

Visually impaired individuals face significant challenges in navigating their environment safely. Though impairments can range in severity, any degree of spatial unawareness poses an issue. The issue may be a slight inconvenience at the very least, and serious injury in worse cases [1] [2]. The continuing growth autonomous vehicles [3] and foot traffic increases the possibility of an accident for those in transit, whether they are impaired or not. In densely populated areas such as New York City, it can prove challenging for visually impaired individuals to commute with their white cane alone. The "Third Eye" aims to address these challenges with contemporary solutions made possible by the technological advancements made to date. This smart stick is equipped with a camera module connected to a Raspberry Pi for image processing as well as LoRa module for sending real time data of nearby objects. The system provides real-time assistance through auditory and tactile feedback to the user, enhancing their mobility and independence. Since our device must be completely portable to serve its purpose, the cane includes an onboard power source and LoRa functionality to maintain connectivity in the absence of WiFi.

The hurdles faced by visually impaired individuals extend beyond mere inconvenience; they intersect with the critical need for safety and independence. The prevalence of vehicular and pedestrian traffic, combined with the ever-evolving urban landscape, poses constant threats to those navigating with limited sight. The consequences of spatial unawareness can range from minor inconveniences to life-altering accidents, highlighting the pressing necessity for reliable, advanced aids tailored to the modern world [4].

This innovative crutch design incorporates various advanced modules like gyroscope, accelerometer, ultrasonic, SIM868, and voice controlled by an STM32F103 micro controller. It enables obstacle detection, rapid ground-drop alerts, and voice guidance for the elderly and visually impaired. Additionally, a dedicated mobile app enhances user safety by providing real-time updates on the user's location and security status to their families. This multi functional design not only ensures key safety features but also fosters better communication between users and their families, significantly enhancing independence and peace of mind during solo outings.

Recognizing these challenges as opportunities for technological advancement, the visionaries behind the "Third Eye" have embarked on a mission to redefine mobility for the visually impaired. This groundbreaking smart stick represents a convergence of cutting-edge technology and compassionate innovation, designed specifically to empower individuals with visual impairments to navigate their surroundings confidently and independently.

At the heart of this revolutionary device lies a fusion of sophisticated components meticulously crafted to enhance the user's experience. Equipped with a camera module integrated with a Raspberry Pi for real-time image processing and an LoRa module for sending live feed, the "Third Eye" doesn't just augment the traditional white cane—it transforms it into an intuitive, intelligent tool for navigation.

The seamless integration of auditory and tactile feedback systems ensures that users receive immediate, context-aware information about their surroundings. This real-time assistance offers not just alerts about potential obstacles but also provides spatial cues, enabling users to make informed decisions as they traverse the dynamic urban landscape.

Crucially, recognizing the need for mobility aids to be adaptable and practical, the "Third Eye" is designed to be portable and self-contained. Equipped with an onboard power source and LoRa functionality, this innovative cane ensures connectivity even in environments devoid of WiFi, ensuring uninterrupted support for users wherever they go.

The "Third Eye" isn't just a device—it's a testament to the power of innovation harnessed for the betterment of lives. As it ushers in a new era of accessibility and autonomy, this smart stick stands as a beacon of hope, promising a future where navigating the world is not just a possibility but a fulfilling reality for visually impaired individuals.

II. Goals

The project aims to empower visually impaired individuals with an affordable and adaptable smart stick, merging cutting-edge technology with accessibility. Through real-time object detection and obstacle sensing, it strives to enhance spatial awareness and safety. The intuitive interface designed for auditory and tactile feedback seeks to seamlessly integrate with users' needs. Rigorous testing and user evaluations form the cornerstone, ensuring a dependable and impactful solution for the visually impaired community. The primary objectives of the project are as follows:

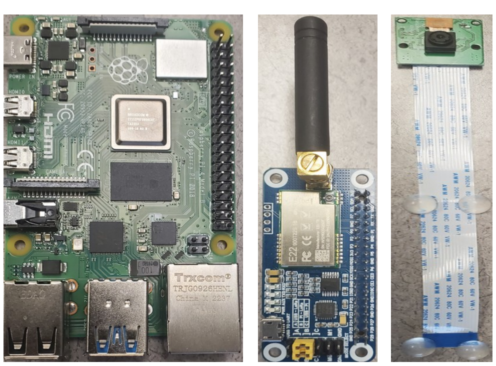
- Develop a cost-effective and portable smart stick for visually impaired individuals.
- Implement real-time object detection using a camera module and Raspberry Pi.
- Integrate LoRa modules to send real time data to receiver.
- Create an intuitive user interface for providing auditory and tactile feedback to the user.
- Conduct extensive testing and user evaluation to ensure the system's reliability and effectiveness.

III. Design

A. Hardware

The hardware of the "Third Eye" smart cane consists of the following components (please refer to the figure 1:

- **Raspberry Pi:** Serves as the central processing unit, running the object detection algorithms and work as the backbone for LoRa modules .
- **Camera Module:** Attached to the Raspberry Pi, used for capturing real-time images for object detection.
- **LoRa Modules:** Integrated with Raspberry pi for sending and receiving data .



a) Raspberrypi Model B   b) LoRA Module   c) Camera Module

Fig. 1. Hardware Equipments for ThirdEye: a)Raspberry Pi ModelB, b)LoRa Module, c)Camera Module

B. Software

The software component involves:

- **Object Detection Algorithm:** Running on the Raspberry Pi, it processes images from the camera module to identify obstacles.
- **Transmitter and Receiver:** Using LoRa with Raspberry pi, it sends object labels to a receiver node.

IV. Implementation

A. Challenges

The biggest task is to run this big model in an edge device like raspberry pi. Intuitively, offloading compute-intense tasks to edge servers can reduce their execution time. However, poor conditions of the wireless channel connecting the mobile devices to the edge servers may degrade the overall capture-to-output delay achieved by edge offloading. Herein, Some papers focused on edge computing supporting remote object detection by means of Deep Neural Networks (DNNs), and developed a framework to reduce the amount of data transmitted over the wireless link. The core idea was to build on recent approaches splitting DNNs into sections - namely head and tail models - executed by the mobile device and edge server, respectively. The wireless link, then, is used to transport the output of the last layer of the head model to the edge server, instead of the DNN input. Most prior work focuses on classification tasks and leaves the DNN structure unaltered. But, their focus was on DNNs for three different object detection tasks, which present a much more convoluted structure, and modify the architecture of the network to: (i) achieve in-network compression by introducing a bottleneck layer in the early layers on the head model, and (ii) prefilter pictures that do not contain objects of interest using a convolutional neural network. [5]

Another challenge in real-time object detection lies in video compression. Most of the deep learning methods use CNNs to process each decoded frame in a video stream individually.However,the free of charge yet valuable motion information already embedded in the video compression format is usually overlooked. In a recent work ,they proposed a fast object detection method by taking advantage of this with a novel Motion aided Memory Network(MMNet). The MMNet has two major advantages:1)It significantly accelerates the procedure of feature extraction for compressed videos.It only needs to run a complete recognition network for I-frames,i.e.a few reference frames in a video,and it produces the features for the following P frames(predictive frames) with a light weight memory network,which runs faster) Unlike existing methods that establish an additional network to model motion of frames, they took full advantage of both motion vectors and residual errors that are freely available in video streams. [6]

B. Setup

The implementation of the "Third Eye" involved several stages . Figure 2 explains the whole setup:

1) **Hardware Assembly:** Building transmitter node with the connection of camera, Raspberry Pi and LoRa module, and receiver node with the connection of another set of Raspberry pi and LoRa module respectively.

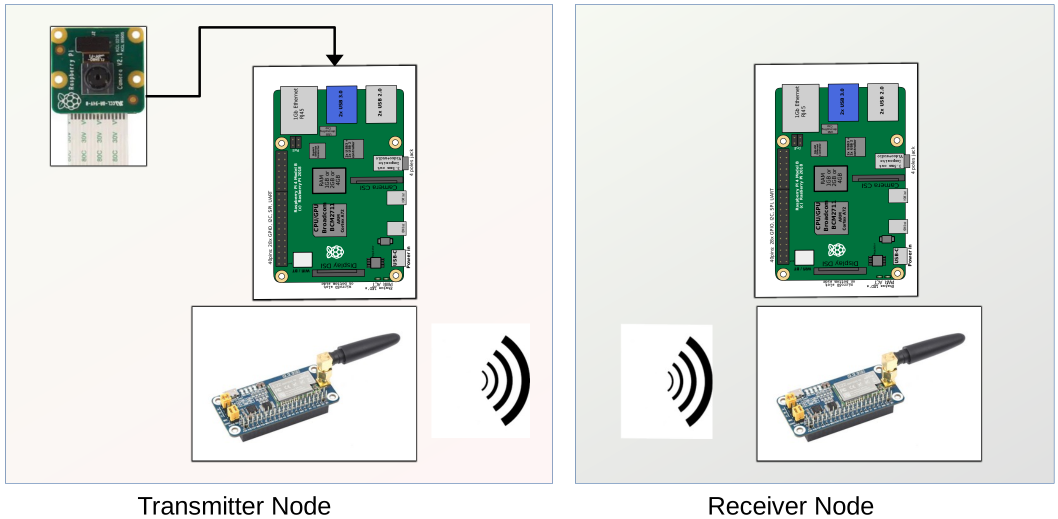


Fig. 2. Schematic Diagram of Transmitter Node and Receiver Node

2) **Software Development:**
   - Developing the object detection module using Python and OpenCV on the Raspberry Pi.
   - Programming the LoRa to send and receive data.
3) **Integration:** Combining the hardware and software components to work in unison, ensuring real-time data processing and feedback.
4) **Calibration:** Adjusting sensor sensitivities and feedback intensity for optimal performance.

C. Floor plan

Figure 3 shows our floor plan where we conducted the experiment. We used our G20 lab for the experiment which is divided into two rooms separated by a wall as shown in the figure. In left side we placed the sender and on the other side we placed the receiver.

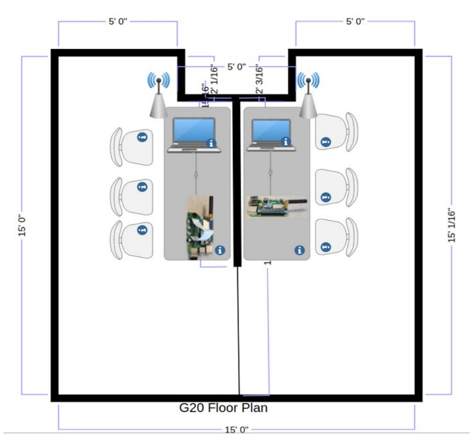


Fig. 3. Floor Plan for Experimentation Setup

V. Experiments

To validate the effectiveness of the "Third Eye," we conducted a series of experiments focusing on object detection accuracy, sensor responsiveness, and user experience. These experiments were designed to test the system under various conditions and gather comprehensive feedback from potential users.

A. Object Detection Accuracy

1) MobileNet V3 Large Model: For real-time object detection, we utilized the MobileNet V3 Large model (please refer to figure4. This model has been improved further on MobileNet v2 by using different loss functions and training techniques like label smoothing (please refer to the tableI).

2) Use of Quantized MobileNet V3 Large Model: For efficient real-time object detection, we utilized a quantized version of the MobileNet V3 Large model. Model quantization is a process that converts a full-precision model (float32) into a reduced precision (int8 or float16), which significantly reduces the model size and computational demand without substantially compromising accuracy. This approach is particularly advantageous for deployment on resource-constrained devices like the Raspberry Pi (please refer to tableII), where computational efficiency is crucial.

a) Quantization Process: The quantization process involved two primary steps: training the full-precision MobileNet V3 Large model on our dataset and then applying post-training quantization. The latter step includes converting the weights and activations of the neural network from floating-point to integer representations, which accelerates inference time and reduces memory usage.

b) Quantization Benefits: By quantizing the MobileNet V3 Large model, we achieved a notable reduction in model size, making it feasible to run the model directly on the Raspberry Pi without external computational resources. Addition-

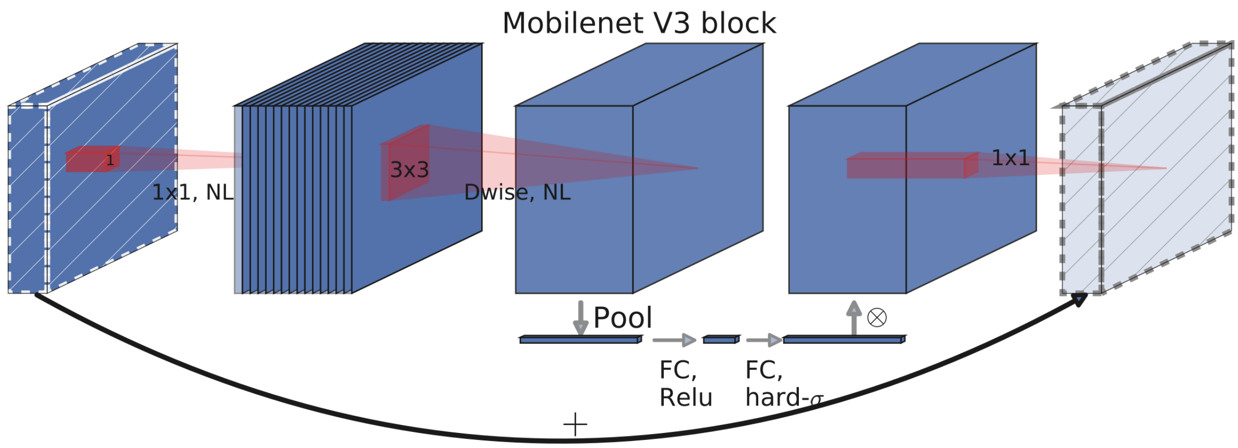


Fig. 4. MobileNet V3 Large model Architecture [7]

TABLE I
ACCURACIES OF DIFFERENT ITERATIONS

Iteration	Acc@1 (%)	Acc@5 (%)
Baseline with "MobileNetV2-style" Hyperparams	71.542	90.068
+ RMSProp with default eps	70.684	89.38
+ RMSProp with adjusted eps & LR scheme	71.764	90.178
+ Data Augmentation & Tuned Hyperparams	73.86	91.292
+ Checkpoint Averaging	74.028	91.382
+ Label Smoothing & Stochastic Depth & LR noise	75.536	92.368

TABLE II
PERFORMANCE COMPARISON OF DIFFERENT MODELS

Model	Acc@1 (%)	Acc@5 (%)	Inference on CPU (sec)	# Params (M)
MobileNetV3-Large	74.042	91.340	0.0411	5.48
MobileNetV3-Small	67.668	87.402	0.0165	2.54
Quantized MobileNetV3-Large	73.004	90.858	0.0162	2.96
MobileNetV2	71.880	90.290	0.0608	3.50
ResNet50	76.150	92.870	0.2545	25.56
ResNet18	69.760	89.080	0.1032	11.69

ally, the quantized model showed a significant improvement in inference speed compared to its full-precision counterpart, which is critical for real-time object detection in assistive devices.

3) Experimental Setup: We deployed the MobileNet V3 Large model on a Raspberry Pi connected to a standard camera module. The setup was tested in different environments, including indoor settings with controlled lighting and outdoor settings with varying light conditions.

4) Procedure: Objects commonly encountered in urban and domestic environments were selected as test subjects, including street signs, vehicles, furniture, and personal items. The model's performance was evaluated based on its ability to accurately detect and classify these objects at various distances and angles.

5) Metrics: The accuracy of the model was quantified using standard metrics: precision, recall, and F1-score. Each metric provided insight into the model's performance, particularly its ability to minimize false positives and false negatives.

B. LoRa Responsiveness

In tandem with visual object detection, the "Third Eye" employs a LoRa modules to send the detected object labels to a safe place. It ensures the long range area coverage with end-to-end energy efficient of the blind person and acts truly as Third Eye for that person. Instead of using small range network coverage like, Bluetooth, WiFi etc LoRa covers at most 5km. Although, latency of the receiver goes down substantially 5.

1) Experimental Setup: A series of closed environment with controlled tests were conducted in a lab environment, where we tested the latency and outputs of LoRa modules over different distances. After rigorous running of our experiment, we found that latency of sender and receiver do not substantially increase for the 5 feet, 10 feet and 15 feet. But it started increasing in 20 feet distance which takes more than 70 millisecond which has been shown in the figure 5.

2) Procedure: We used two LoRa modules, one as sender node with raspberry pi 4 model B and another as receiver node with another raspberry pi 4 model B. After running our

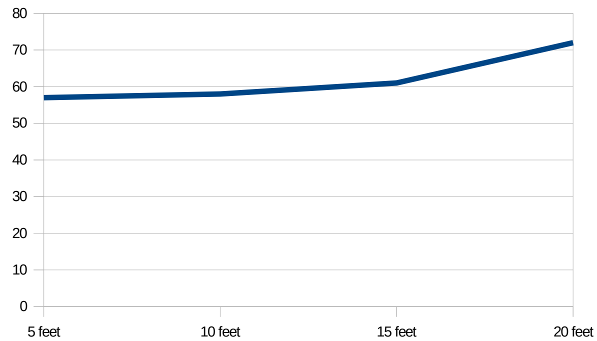


Fig. 5. Latency of Source to Receiver

MobileNet V3 model, the LoRa module starts sending the object labels to the receiver as they are detected by the camera in real time.

3) Metrics: The key metrics for this experiment included detection range accuracy and response latency.

VI. Related Work

Several projects and research efforts share our focus on assistive technologies for the visually impaired, each contributing a distinct approach to the problem. One such example is the City College of New York "SmartCane" [8].

This variation of the smart cane features a navigation system capable of mapping indoor routes for its users. Though conceptually similar to the "Third Eye," the "SmartCane" implementation differs in its technological components, namely Google Tango. The now-discontinued augmented reality platform was used by CCNY to map indoor spaces and the user's position in the space. We hope to expand the indoor limitations of the "SmartCane" to a larger environment.

Real-time feedback is a crucial component of our approach and that of others. Mahmud's navigation system addresses this component through generated vibrations and voice messages [9]. Jin's smart cane also uses a vibration motor but uses the feedback for an interesting feature: facial recognition. The cane is connected by Bluetooth to a camera mounted on a pair of glasses worn by the user. The camera takes a picture of the person in front of the user, and once the face is detected, the user is notified of the person's identity by a pattern of vibrations made by the cane [10].

Developed an IoT-enabled smart stick for visually impaired individuals to navigate their surroundings while detecting and warning about obstacles. The smart stick uses ultrasonic sensors for obstacle detection, a water sensor to identify wet surfaces, and a high-definition camera for object recognition. Users receive voice feedback through earphones, which accurately detects and identifies objects. The smart stick offers two modes: one with vibration feedback from ultrasonic sensors and another with voice feedback for obstacle recognition. The system also tracks the user's location through GPS/GSM modules and provides a panic button for emergency assistance. It is designed to be lightweight, waterproof, size-adjustable, and energy-efficient, emphasizing portability, stability, and robust features. [11]

RFID tags have gained significance as sensors for various applications such as home automation, health monitoring, and augmented reality. However, their extensive use as sensors has been hindered by the need for complex equipment like tethered readers, limiting their mobility. To address this issue, we introduce WearID, a low-power wrist-worn backscatter reader. This innovation significantly enhances the usability of RFID sensors for detecting interactions with tagged objects. WearID incorporates advancements in both hardware and signal processing, resulting in remarkable efficiency and performance improvements. Compared to state-of-the-art commercial readers, WearID consumes six times less power, offers 3D coverage around the wrist despite body blockage, and reliably identifies various hand-based interactions. Additionally, we have made the WearID design open source to encourage the exploration of new wearable applications [12].

The conventional method of demodulation fails to utilize the characteristics of signals resulting in a less than optimal threshold for signal to noise ratio (SNR) which leads to decoding failures. As a result compromises have to be made in terms of communication range and energy consumption to ensure transmission. To extract crisp symbols NELoRa has been proposed where a neural network enhanced LoRa demodulation method is used by enabling the feature extraction of Deep Neural Network (DNN) in ultra-low SNR LoRa communication. NELoRa combines a dual channel spectrogram to a multidimensional feature space where multidimension contains not only amplitude but also phase. A chirp-level data synthesis approach is incorporated into NELoRa to improve its capacity to generalize for different deployment scenarios. Their results increase the battery life of different NELoRa configurations by about 1.5 years [13].

Protean which is a versatile framework designed to accelerate the prototyping and deployment of resilient, adaptable, and inference-powered energy harvesting applications, all without the need for batteries. An open-source hardware platform called SuperSensor provides modular plug-and-play functionality which is more energy efficient incase of energy storage and energy measurement. It consists of one processor module based on ARM Cortex MCU with a hardware accelerator, two harvester modules and five peripheral modules consisting of six sensors and two communication modalities. For dynamically switching, they used Chameleon. Metamorph is being used to take user inputs, standard CNN models and output the implementation. Protean shows a 666x improvement with audio and image workload in energy efficiency by intermittent computing. [14]

To mitigate the effects of device motions and enable sensing while the device is in motion RobotSen has been proposed. The approach leverages signal propagation theory to understand the impact of device motion on signal variations and uses a second antenna to eliminate motion-induced signal changes. This design allows the robot to achieve accurate sensing while the robot is in motion, advancing the feasibility of ubiquitous wireless sensing for real-world applications. The key contributions of this work include combining LoRa sensing with robot mobility for extended sensing coverage, proposing a novel method to eliminate signal variation caused by device motion, and evaluating the system's performance in two representative applications. While our implementation uses LoRa hardware, the proposed method can be applied to other wireless sensing modalities as well. Their experiments demonstrate the effectiveness of our system in two sensing applications: fine-grained respiration monitoring and coarse-grained human walking sensing, even in the presence of device motions. [15]

Rather than developing a cane with built-in smart functionality, Mutiara instead proposed an extension module for regular white canes. Similarly to the ”Third Eye,” the ”Smart Guide Extension” module uses Arduino to inspect the user's surroundings. Mutiara's prototype, however, includes wind direction detection, a unique addition. [14]

By consolidating desirable features of similar devices and making additions of our own, our project aims to develop an improved smart cane design.

Object detection, as of one the most fundamental and challenging problems in computer vision, has received great attention in recent years. Over the past two decades, we have seen a rapid technological evolution of object detection and its profound impact on the entire computer vision field. If we consider today's object detection technique as a revolution driven by deep learning, then, back in the 1990s, we would see the ingenious thinking and long-term perspective design of early computer vision. Some articles extensively reviews this fast moving research field in the light of technical evolution, spanning over a quarter-century's time (from the 1990s to 2022). A number of topics have been covered in some articles, including the milestone detectors in history, detection data sets, metrics, fundamental building blocks of the detection system, speedup techniques, and recent state-of-the-art detection methods. [16], [17]

Object detection models are very heavy in terms of computational requirements. Despite significant accuracy improvement in convolutional neural networks(CNN) based object detectors,they often require prohibitive run times to process an image for real-time applications.State-of-the-art models often use very deep networks with a large number of floating point operations.Efforts such as model compression learn compact models with fewer number of parameters,but with much reduced accuracy.In some works,they proposed a new frame work to learn compact and fast object detection networks with improved accuracy using knowledge distillation. and hint learning. [18]

VII. Lessons Learned

This project has provided several valuable insights into the development of assistive technology for the visually impaired. Key lessons learned include:

- **Importance of User-Centric Design:** Direct feedback from visually impaired users was crucial in shaping the design and functionality of the ”Third Eye.” This user-centric approach ensured that the device met actual needs rather than presumed requirements.
- **Balancing Performance and Efficiency:** Employing advanced technologies like the MobileNet V3 model and quantization techniques has underlined the importance of balancing computational performance with efficiency, particularly for portable, battery-powered devices.
- **Integrated Expertise:** The development of the ”Third Eye” was a multidisciplinary effort, combining expertise in computer vision and long area network coverage in energy efficient manner. This combination of approach was key to addressing the multifaceted challenges of the project.
- **Real-World Testing:** Field tests played a critical role in understanding the practical challenges faced by users, leading to iterative improvements in the device.

These lessons not only informed the current project but also provide valuable guidelines for future work in the field of assistive technologies.

VIII. Conclusion and Future Work

In conclusion, the ”Third Eye” project represents a significant step forward in assistive technology for the visually impaired. By leveraging advanced object detection algorithms and responsive sensor technology, the device offers a new level of independence and safety for its users.

A. Future Work

Looking ahead, there are several avenues for further development:

- **Sending Video Stream Over LoRa :** In our current work we are able to send the object labels to the receiver but in future if we could send the video stream directly through LoRa that would be even more advanced system.
- **Integration with Other Technologies:** Future versions of the ”Third Eye” could incorporate additional technologies such as GPS navigation and machine learning-based auditory systems for enhanced spatial awareness and user interaction.
- **Expanded Object Database:** Expanding the database used for object detection will make the device more versatile and useful in a wider range of environments.
- **Connectivity Features:** Implementing features such as Bluetooth connectivity for smartphone integration could offer additional functionalities like remote assistance and location tracking.
- **Long-Term User Studies:** Conducting long-term studies with a larger group of users will provide deeper insights into the device's impact and areas for improvement.

The ”Third Eye” project, with its innovative approach and positive user feedback, lays a strong foundation for future advancements in assistive technologies for the visually impaired.

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