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Original Research

IoT Enabled Automated Object Recognition for the Visually Impaired

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ABSTRACT

Background: Visual impairments have become one of the most predominant problems for the last few decades. To keep doing their daily tasks, vision-impaired people usually seek help from others. An automated common object and currency recognition system can improve the safe movement and transaction activity of visually impaired people.

Objective: To develop a system that can identify indoor and outdoor objects, notify the users, and send all information to a remote server repeatedly at a fixed time interval.

Methods: The proposed system assists the visually impaired to recognize several objects and provides an audio message to aware the user. Four laser sensors are used in the system to detect the objects in the direction of the front, left, right and ground. The proposed system uses Single Shot Detector (SSD) model with MobileNet and Tensorflow-lite to recognize objects along with the currency note in the real-time scenario in both indoor and outdoor environments.

Results: Among 375 participants, 82% reacted that the price of the proposed system is reasonable, 13% treated as the cost is moderate and the rest 5% people responded that the cost is relatively high for them. In terms of size and weight, 73% reacted that the size and weight are considerable, 20% treated that the size is not suitable, and weight needs to lessen, and the rest 7% people responded that the system is bulky. Regarding input signal observation, 98% responded that they have heard the sound appropriately and the remaining 2% of individuals missed hearing the signal.

Conclusions: This paper represents an IoT-enabled automated object recognition system that simplifies the mobility problems of the visually impaired in indoor and outdoor environments. The overall accuracy of the proposed system in object detection and recognition is 99.31% and 98.43% respectively. In addition, the proposed system sends all processed data to a remote server through IoT.

1. Introduction

The statistics of the World Health Organization (WHO) shows that the number of visually impaired is growing day by day. On average, the number of visually impaired is 285 million of whom 39 million are sightless and the rest 217 million are suffering from low vision [1]. To keep doing their daily tasks, vision-impaired people usually seek help from others. And the most noteworthy part is when they explore a new place they should understand the barriers' position and other objects in their course for their safe navigation [2,3]. Secure and safe mobility is one of the most demanding events faced by vision-impaired people in the real-life environment [4]. Being unable to track out and avoid blockage in their course, most often they become the victim of some unwanted troubles that might lead them to emotive misery or unasked incidents and their frequent mobility is being undercut [5,6]. So they need assistance from others or assistive devices to complete their day-to-day tasks including uninterrupted navigation and so on [7]. However, ensuring secure and safe mobility for the visually impaired is a complex task that requires precision and effectiveness.

One of the other serious issues, that are being faced by the visually impaired, is to recognize currency because of the likeness of paper surface and size among various classes [8]. At the same time, visually impaired people are facing serious issues with newly released notes' sizes and colors [9]. For example, the new 50 BDT and 200 BDT notes have identical colors, making it difficult for persons with low vision to identify and make appropriate transactions. This problem makes a great suffer in their daily activities when they deal with currencies [10]. Identifying staircases is another matter of concern for the visually impaired since the failure to identify them can cause serious damages [11]. Without seeing the stair, it is quite impossible to perfectly identify the edges

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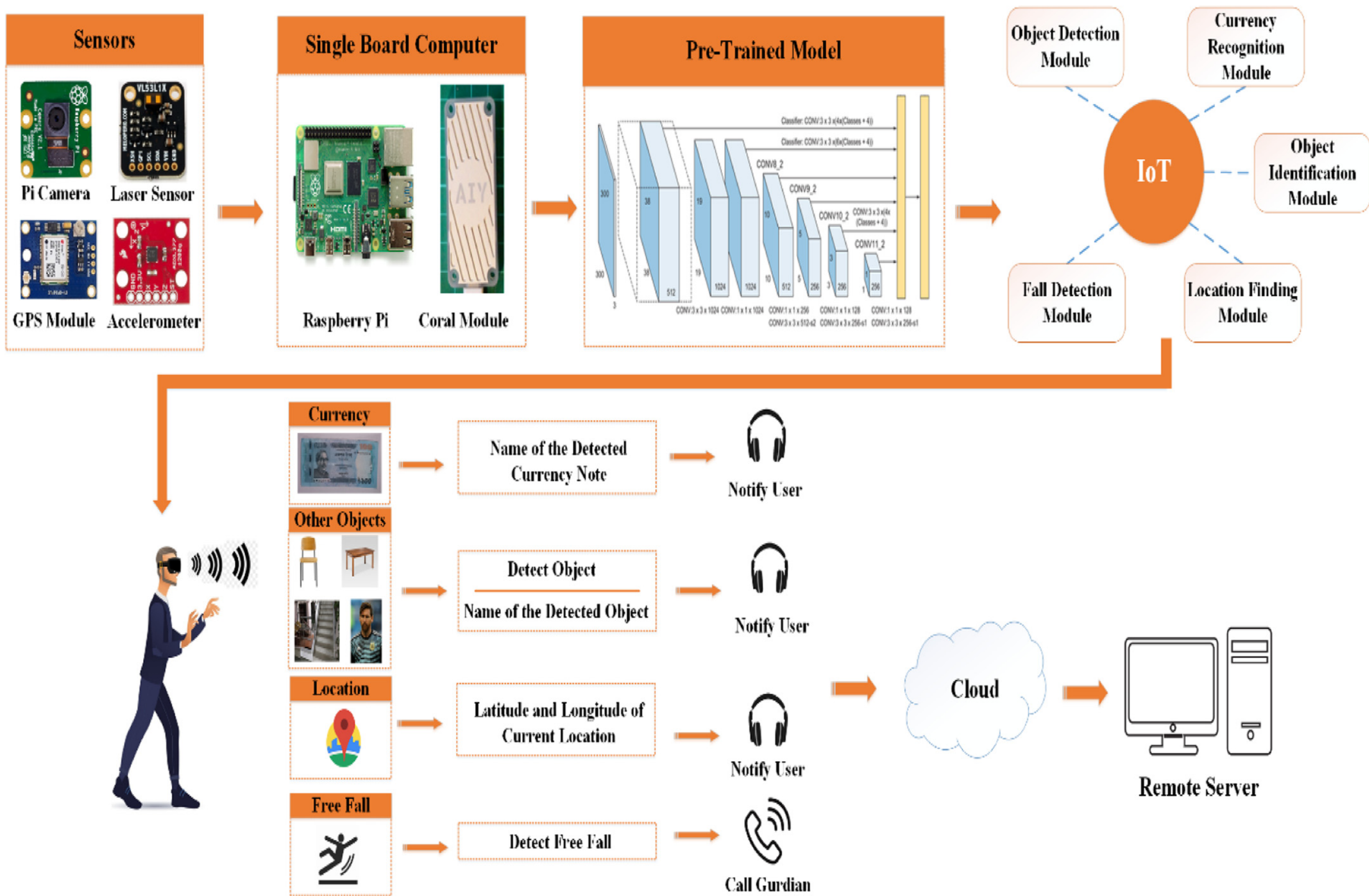


Fig. 1. Overall system architecture of the proposed system.

of every plate of a stair [12]. Among other problems, faced by people with visual disabilities, recognizing washrooms, chairs, tables, persons, etc. are mentionable.

In this paper, we have introduced an IoT-enabled automatic object recognition system that simplifies the mobility problems of the users by secure movement in indoor and outdoor aspects. The proposed system assists the visually impaired to recognize several objects such as a person, chair, table, washroom, currency, etc. which the visually impaired cannot identify generally. Moreover, the proposed system is developed with a low budget and a person can carry it easily which helps the users to do their daily activities smoothly.

The remainder of the paper is coordinated as follows. The proposed methodology for object and currency recognition utilizing sensors, Mobile Net and SSD is exhibited in Section 2. The implementation details of the prototype are depicted in Section 3. The experimental analysis of the developed system is illustrated in Section 4. Section 5 depicts the discussion of this research. The paper concludes with Section 6.

2. Methods

The main methodology of the proposed system is divided into five modules- a) Object Detection, b) Object Recognition, c) Fall Detection, d) Location Finding, and e) IoT-enabled automated system. The sensor-based obstacle detection method is used in the Object Detection module. Single Shot Detector (SSD) model with MobileNet is used to perform the recognition with high accuracy and processing speed. The currency recognition module uses the SIFT algorithm to recognize currency notes currently running in Bangladesh. The processed data of the above three modules are sent to a remote server for further analysis through an IoT-enabled module. The architecture of the proposed system is shown in Fig. 1.

2.1. Object Detection Module

In the proposed system, four laser sensors (VL53L1X) are used for object detection. This module uses three sensors to detect objects in the left, right, and front direction, and another sensor is used for detecting ground or knee level objects. These sensors are capable to detect objects in the range of 400 cm and use the time of flight (ToF) technology. It incorporates a SPAD getting array, a 940 nm imperceptible Class 1 laser producer, actual infrared channels, and optics to accomplish the best ranging presentation in different surrounding's lighting conditions. The VL53L1X utilizes ST's most recent ToF innovation which permits supreme distance estimation whatever the objective color and reflectance is.

The distance is calculated by using the triangulation of the beam of light as shown in (1). The sensor produces a laser light shaft that hits an object at an occurrence point, reflects from it, and is distinguished. A triangle is framed between the laser source (TX), the measured object, and the detector (RX). By estimating the specific area where the laser hits the locator, distance is determined with basic mathematics.

$$Distance = (speed\ of\ light \times elapsed\ time) \quad (1)$$

In order to ensure safe movement and avoid collisions, we have chosen a threshold or limit of distance between the user and the objects based on the moving speed of the sightless people. The threshold value is 150 cm. The object detection within the threshold range is shown in Fig. 2.

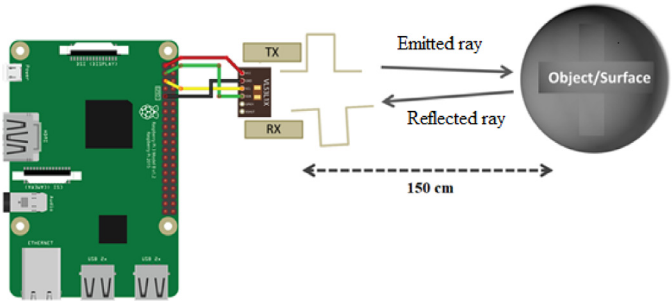


Fig. 2. Object Detection within the Threshold Range.

2.2. Object Recognition Module

The object recognition module is separated into two parts. Those are-Common Object Recognition and Currency Recognition. The Raspberry Pi and Pi camera are used in the object recognition module to recognize objects in both indoor and outdoor environments.

2.2.1. Common Object Recognition

The proposed system identifies several types of objects such as staircase, chair, table, person, washroom, etc. The overall process of this phase is discussed shortly in the flowing steps.

2.2.1.1. Image Capturing. Image capturing is the initial phase of the object recognition module. The Pi camera module v2 is used to capture the images from the environment. In the proposed system, the pi camera is attached to the front side of the prototype. The real-time instance is captured as a frame. In order to reduce the processing cycle, we have chosen a fixed resolution for each frame which is 720×680 pixels. Then the frame is sent to the feature extractor for further operations. Fig. 3(a) shows the interconnection between the pi camera module and Raspberry pi and Fig. 3(b) shows the captured image by the camera.

2.2.1.2. Feature Extraction. In the proposed framework, MobileNet [13] is utilized to extricate the features of the input frames. MobileNets essentially use depthwise distinguishable convolutions instead of the standard convolutions utilized in initial designs to fabricate lighter models.

2.2.1.3. Dataset Creation and Augmentation. In the proposed system, we have used two separate datasets. One is for common object recognition and another is for currency recognition. We have created our custom dataset in the same format as the MS COCO dataset [14].

- ***Data Collection.*** We have collected various images of persons, chairs, tables, stairs, and washrooms, etc. mainly from the campus of Khulna University of Engineering & Technology, Khulna. The images of the banknote are collected from the Janata Bank, KUET branch, Khulna. At the time of data collection, it is ensured that all of the images are of same height, and width, and are less noisy.
- ***Data Augmentation.*** All images are augmented in this phase to fulfill the collection of images and to perform more accurate object detection. Several augmentation methods are used to augment the images such as horizontal flipping, vertical flipping, rotating, mirroring, zooming, etc. We have generated a total of 4500 images from the augmentation technique. Then we have partitioned the dataset into training and testing segments. The training segment contains 4300 images and the testing segment contains 200 images.
- ***Data Annotation.*** The “LabelImg” tool [15] is used to annotate the images in the proposed system. The “LabelImg” tool provides an XML document for each image after annotation. Each XML file contains the object name, size, and coordinate of a bounding box (x-min, y-min, x-max, y-max) of the object.

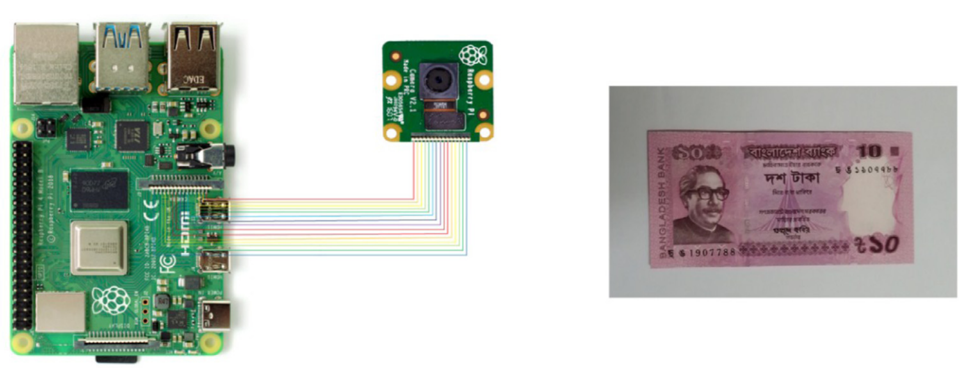
In the proposed system, a PASCAL VOC format dataset is created first from the XML documents and a text file which contains the class name of all objects. Then a PASCAL to COCO converter is used to convert PASCAL VOC format to COCO format. The created dataset contains five classes for the five types of objects and finally, this dataset is used to train the object recognition model.

2.2.1.4. Training and Testing. In the proposed system, a pre-trained model is used to identify objects due to the lack of processing power and GPU support of raspberry pi. The model is trained first on a GPU-enabled CPU using the created custom dataset. The training proceeds with 2000 iterations while the weights are saved after every 500 iterations. After the training process is over, the last saved weight and the class file are passed to the raspberry pi. Then, the testing set is used to check the performance of the trained network.

2.2.1.5. Detector. In the proposed system, Single Shot Detector (SSD) [16] network is used as a detector. The SSD uses convolutional layers of varying sizes and a fixed set of default bounding boxes. The object localization and classification are done in a single forward pass of the network which runs at 59 FPS. Fig. 4 represents the basic architecture of SSD in a 300×300 input image.

2.2.2. Currency Recognition

We have created another dataset for currency recognition. In Bangladesh, eight common bank notes are running currently such as Five, Ten, Twenty, Fifty, One hundred, Two hundred, Five hundred, and One thousand taka. At least 100 images are taken for each banknote. So a total of 800 images are used to create the dataset. A python script is used to generate a weight file that contains features (key points) for each image.



(a) (b)

Fig. 3. (a) Camera interfacing with raspberry pi, (b) Captured image.

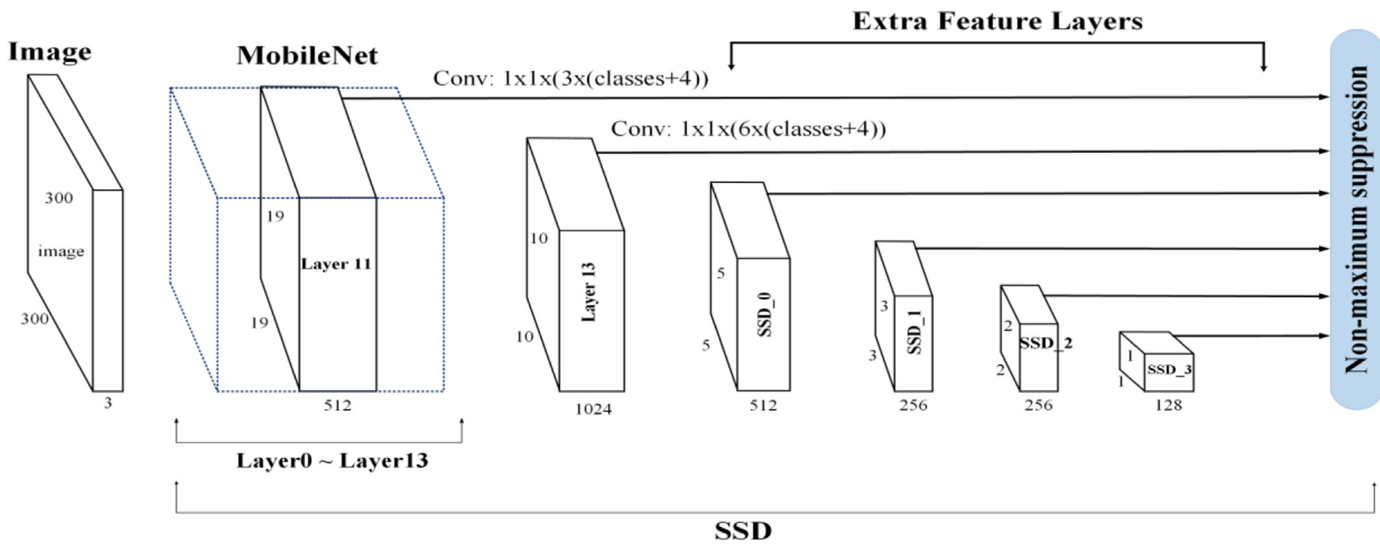


Fig. 4. SSD in 300 × 300 Input Image [47].

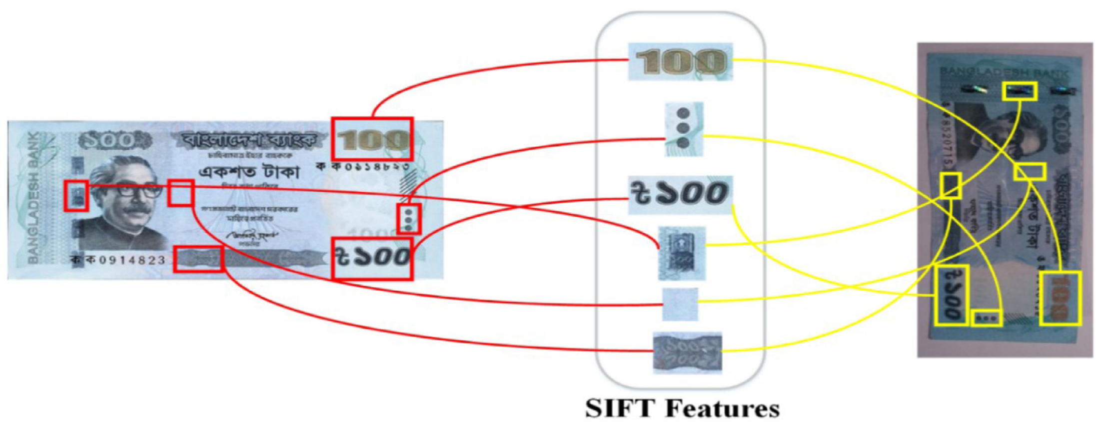


Fig. 5. An example of Feature extraction by SIFT algorithm.

In the proposed system, Scale Invariant Feature Transform (SIFT) [17] is used for currency recognition. The SIFT algorithm locates the local features of the currency notes, commonly known as the 'key points' of the notes. Finally, these key points are used for currency recognition. An example of Feature extraction by SIFT algorithm is shown in Fig. 5. In the figure, the same currency note (100 taka) is placed in two different directions and different light intensities. Several local features of that currency note are located by the algorithm and marked those features as 'key points' to identify the note. In Fig. 5, we have shown just an example to understand the algorithm, not the exact internal procedure of the SIFT algorithm.

2.3. Fall Detection Module

Falls have become a major problem for the visually impaired because they may cause significant illness and mortality. This is due to the complications arising from falls causing a significant decrease in serious injury, and an increase in the utilization of medical services. The proposed system can detect the free fall and alert the guardian when the free fall has been occurred.

The proposed system uses an accelerometer (ADXL345) to detect the free fall. The ADXL345 is a little, slim, low-power, 3-axis accelerometer. It estimates dynamic acceleration because of movement or stun. The FREE_FALL bit is set when the acceleration is not exactly the value put away in the THRESH_FF register (Address 0 × 28) is capable of additional time than is indicated in the TIME_FF register (Address 0 × 29).).

Subsequent to getting information from the accelerometer, the information preparing stage handles the analog to digital signal change and memory allocation. Moreover, the aftereffects of the information preparing and feature extraction stages are determined utilizing the fall identification calculation. The fall identification alarm is arranged into two groups depending on the level of crisis. One is the ordinary fall alert that happens during non-genuine falls, and for this situation, the client can drop the caution by squeezing and holding the emergency fall button. The other is the basic fall caution showing the fall is adequately genuine to cause lethal injury, and in the present circumstance, the faller needs immediate support. If a major injury occurs and the victim cannot stop the alarm then it will be considered a serious fall.

2.4. Location Finding Module

In the proposed system, a GPS module is used to find the city, state, and country names of the current location. A push button is attached in the proposed prototype to enable or disable the location finding module. When the push button is pushed, the GPS module starts to receive data from four different satellites. The system uses the received data and gets the latitude and longitude of the current location. A python script is used to decode the latitude and longitude in

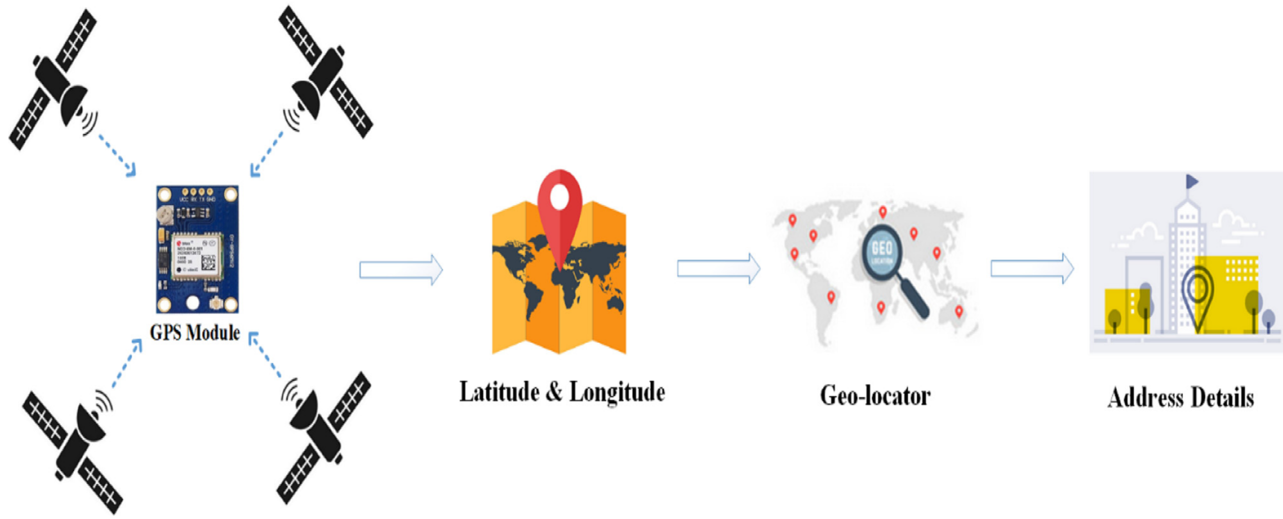


Fig. 6. Location finding procedure.

order to get the city, state, and country names of that location. The location finding procedure of an unknown location is illustrated in Fig. 6.

2.5. IoT-Enabled Automated Object Recognition System

All the modules of the proposed system are connected to the internet. So the system can send all sensors' data and information from the above modules to a remote server which is hosted in "EbnHost". A real-time database in the remote server is created to store the information which is sent from the proposed system for further analysis. A webpage in the remote server handles the POST operation from the raspberry pi. To maintain security and integrity, the proposed system handles a local server along with the remote server. The data from the above modules are saved first in the database of the local server through "XAMPP". A small change in the local database is triggered the remote database to store the new information.

In the proposed system, the data from the real-world environment is collected by the laser sensor, accelerometer, GPS module, and pi camera as an actuator. The raspberry pi will then be responsible for manipulating the data into a suitable format for transmission. To transmit the data, a GSM modem is attached to the raspberry pi. A Google coral dev module is also connected to the raspberry pi to speed up the system.

3. System Implementation

The proposed system consists of four laser sensors (VL53L1X), one Pi camera, accelerometer, GPS module, Raspberry Pi, power supply, Coral dev module, GSM modem, and a spectacle prototype. The laser sensors are used for object detection in the direction of left, right, front and ground. The Pi camera is used to capture images and to provide video streams for real-time operations. In this system, the 8MP V2 Pi camera has used for better performance and placed in the middle of the front side of the prototype. The circuit diagram of the proposed system is shown in Fig. 7.

In order to create the pre-trained model, a high configurational computer is used in this system. The computer is powered by a 10th generation Intel Core i7 processor. The processor comprises 8 Cores, 16 MB Cache, and 2.30 GHz base frequency with 16GB RAM. A GeForce GTX 1650 OC 4GB GDDR6 Graphics Card is also attached with the motherboard. In the proposed system, a Raspberry Pi 4 Model B is used as a single board computer. We have used Pi with 8GB RAM that is the highest configuration for the latest Raspberry Pi. A coral dev module is also interfaced with the Pi for better processing speed and frame rate for object recognition.

The main material of the spectacle prototype, which is used in the proposed system, is rubber. An elastic band is used at the backside of the prototype that makes it suitable for visually impaired people even they fall, the spectacle will remain in their head. The length of the frame is 15 cm and the width is 15.24 cm. In this spectacle, four holes are used for four laser sensors at the direction of left, right, front, and ground facing. In order to attach the Pi camera, one hole is created on the front side of the prototype. Four push buttons are positioned at the top side of the prototype whose are used for four different purpose such as- currency and location buttons are for enabling or disable the currency recognition module and location finding module respectively, the alarm and power buttons are used to turn off or on non-serious alarm and power of the prototype respectively.

Bluetooth technology is used to communicate between user headphones and the proposed spectacle. The system provides an audio signal to the user based on the presence of the obstacles in the direction of left, right, and front. If no object is found in any direction, then the system can guide the user in any direction chosen by the user.

4. Experimental Results Analysis

The performance of the proposed system is evaluated in the domain of object detection and object recognition in both indoor and outdoor environments. The experiment was carried out both in indoor and outdoor environments. In both environments, we considered five different objects with eight currency notes for the detection and recognition purpose. These objects are placed at seven different regions for detecting them by the laser sensors. The regions are

Region 1: (0–30 cm)
Region 2: (31–60 cm)
Region 3: (61–90 cm)
Region 4: (91–120 cm)
Region 5: (121–150 cm)
Region 6: (151–180 cm)
Region 7: (181–210 cm)

These regions are created for the direction of left, right, and front of the developed system. We considered the last value for each region such as 30 cm for region1, 60 cm for region 2, similarly 210 cm for the final region. A fixed interval of 30 cm was taken between two regions. To recognize the objects, we considered a single region that is 0–150 cm. It is noted that better accuracy is gained at the position between 30 and 50 cm for currency notes.

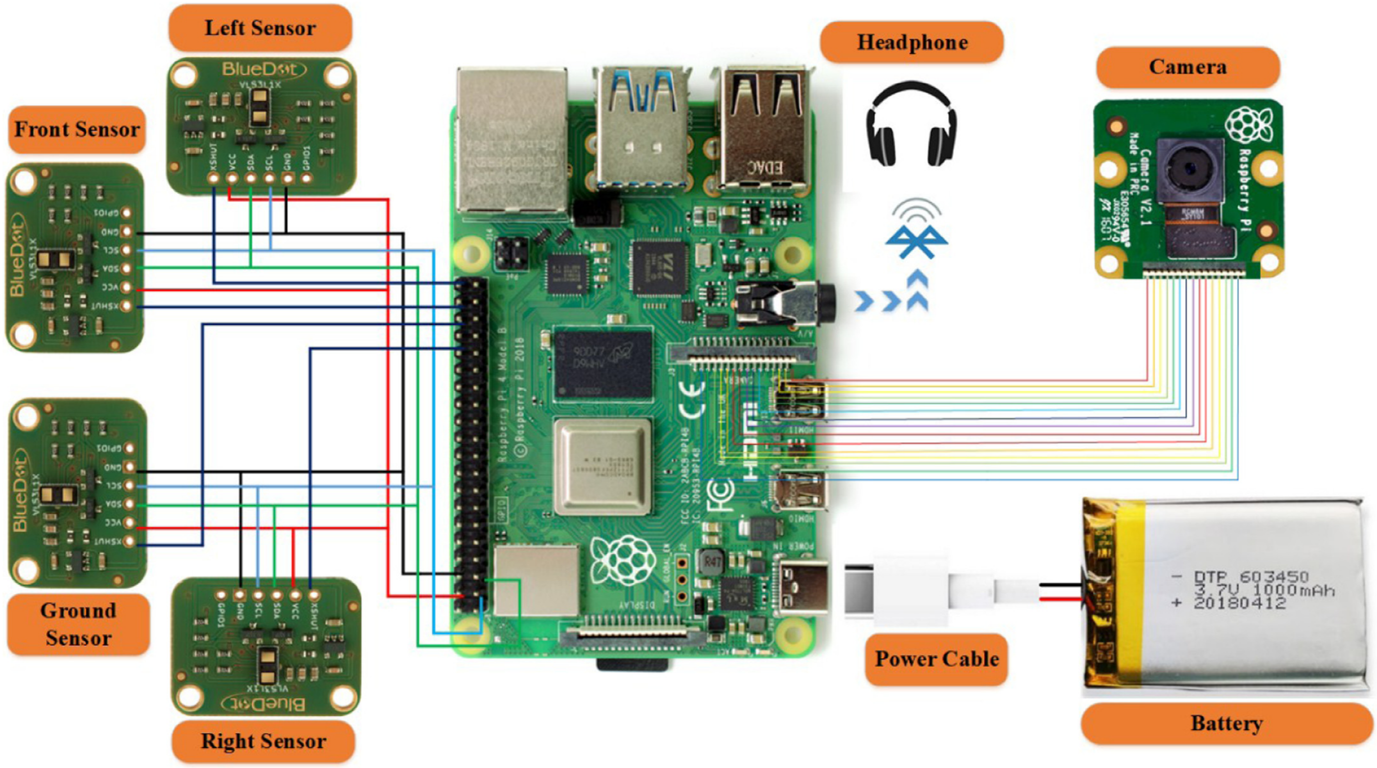


Fig. 7. Circuit diagram of the proposed system.

Table 1
- Distance measurement at indoor environment.

Actual Distance (cm)	Measured Distance (cm)										Average(cm)
	1	2	3	4	5	6	7	8	9	10	
30	30.00	31.00	29.00	30.00	31.00	30.00	31.00	30.00	30.00	31.00	30.30
60	60.00	58.00	61.00	58.00	60.00	59.00	61.00	59.00	60.00	59.00	59.90
90	91.00	90.00	92.00	90.00	90.00	87.00	91.00	89.00	90.00	88.00	89.80
120	119.00	119.00	119.00	118.00	119.00	117.00	120.00	119.00	120.00	119.00	118.90
150	150.00	151.00	151.00	150.00	151.00	151.00	150.00	150.00	151.00	150.00	150.50
180	180.00	179.00	180.00	180.00	180.00	179.00	180.00	178.00	177.00	180.00	179.30
210	209.00	208.00	209.00	209.00	209.00	208.00	209.00	209.00	209.00	209.00	208.80

Table 2
Object detection performance of indoor environment.

Actual Distance (cm)	Average(cm)	Accuracy(%)	Error rate (%)	Standard Deviation	Variance
30	30.30	99.00	1.00	0.64	0.41
60	59.90	99.83	0.17	1.10	1.22
90	89.80	99.77	0.23	1.40	1.69
120	118.90	99.08	0.92	0.83	0.69
150	150.50	99.66	0.34	0.50	0.25
180	179.30	99.61	0.39	1.00	1.01
210	208.80	99.42	0.52	0.40	0.16

4.1. Object Detection

To detect objects, we have observed and collected the data from the laser sensors. A fixed number of samples (ten samples) are collected from each region and both indoor and outdoor environments. The values of the measured distance of the indoor environment are illustrated in Table 1. For each region, we have taken the measured values and made a mean value from those values. These mean values of the seven regions are taken for further performance evolution.

The performance of the indoor object detection based on the measured distances from the indoor environment is presented in Table 2. The accuracy, error rate, standard deviation, and variance of the indoor environment are calculated from the average values of Table 1. The average accuracy of this phase is 99.48%. The best accuracy is gained from the distance of 90 cm which is 99.77% in region 2. The average error rate, standard deviation, and variance are 0.62, 0.83, and 0.77 respectively.

The measured distances of each region in the outdoor environment are illustrated in Table 3. We calculated the average value from the ten

Table 3
Distance measurement at outdoor environment.

Actual Distance (cm)	Measured Distance (cm)										Average(cm)
	1	2	3	4	5	6	7	8	9	10	
30	30.00	29.00	29.00	30.00	31.00	30.00	28.00	30.00	30.00	29.00	29.60
60	60.00	58.00	60.00	58.00	60.00	59.00	60.00	58.00	59.00	59.00	59.10
90	91.00	90.00	89.00	88.00	90.00	87.00	91.00	89.00	90.00	88.00	89.30
120	119.00	119.00	118.00	118.00	119.00	117.00	119.00	119.00	120.00	119.00	118.70
150	150.00	149.00	151.00	150.00	148.00	150.00	150.00	149.00	151.00	150.00	149.80
180	180.00	179.00	180.00	180.00	179.00	179.00	180.00	178.00	178.00	179.00	179.20
210	208.00	208.00	209.00	209.00	209.00	208.00	209.00	209.00	208.00	209.00	208.60

Table 4
Object detection performance of outdoor environment.

Actual Distance (cm)	Average(cm)	Accuracy(%)	Error rate (%)	Standard Deviation	Variance
30	29.60	98.66	1.34	0.80	0.64
60	59.10	98.50	1.50	0.83	0.69
90	89.30	99.22	0.78	1.26	1.61
120	118.70	98.92	1.08	0.78	0.61
150	149.80	99.87	0.13	0.87	0.76
180	179.20	99.56	0.44	0.74	0.56
210	208.60	99.33	0.67	0.48	0.24

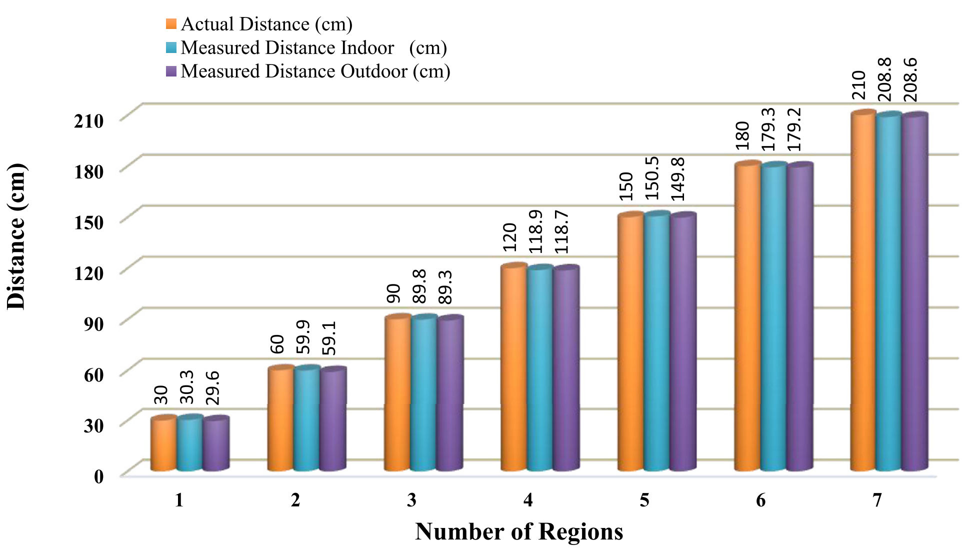


Fig. 8. Comparison of measured distance between indoor and outdoor environment.

samples of each region. It is noted that each case of these ten samples is the average of three laser sensors in the direction of left, right, and front. The performance of the object detection in the outdoor environment is shown in Table 4. Table 4 represents the accuracy, error rate, standard deviation, and variance of the object detection module for the outdoor environment. The average accuracy of this phase is 99.15%. The highest accuracy is gained from region 5 which is 99.87%. The average error rate, standard deviation, and variance are 0.85, 0.82, and 0.73 respectively.

The comparison between the indoor and outdoor environment about the measured distance is depicted in Fig. 8. From the figure, it can be observed that the measured distances of each region are so close in both environments. In regions 6, 4, and 7, the difference between the two environments is 0.1 and 0.2 respectively. However, the distances measured in the indoor environment are less distorted than the distances measured in the outdoor environment from the actual distance.

Accuracy is the most powerful and relevant parameter to measure the performance of a system. The accuracy of the indoor and outdoor environment is 99.48% and 99.15% respectively and the overall accuracy of the developed system is 99.31%. The comparison of accuracy between indoor and outdoor environments is illustrated in Fig. 9. It exhibits that the accuracy of the indoor environment is better and more accurate than the accuracy of the outdoor environment. Among the seven regions, only in region five, the outdoor accuracy is more than the indoor accuracy.

The error rate is a performance measurement parameter that is the opposite of the accuracy. Fig. 10 depicts the error rate of the developed system. The overall error rate of the system is 0.74 where the error rate of the indoor environment is 0.62 and 0.85 is for the outdoor environment. The highest error rate of the indoor and outdoor environment is 1.00 and 1.50 found in the region 1 and 2 respectively. From Fig. 10, it is clear that the object detection module works better in the indoor environment.

Standard deviation is a significant parameter for performance estimation in a distribution. Actually, the standard deviation is the square root of the arithmetic mean of the squares of deviations of perceptions from their mean value. The lower estimation of standard deviation portrays the smaller deviation from the mean value. The comparison of standard deviation between the indoor and outdoor environment is illustrated in Fig. 11. The lowest standard deviation is found in region

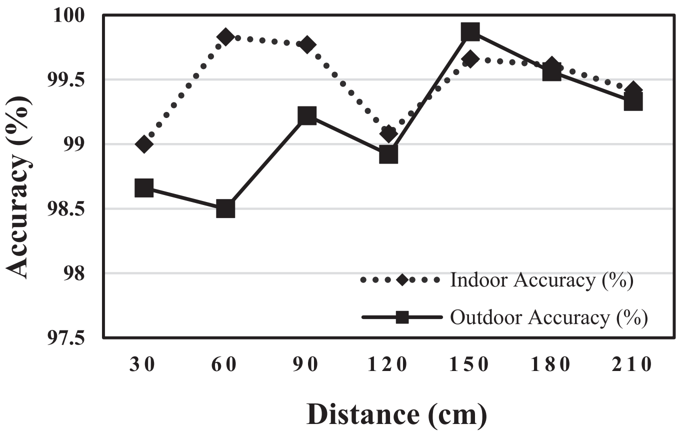


Fig. 9. Comparison of accuracy between indoor and outdoor environment.

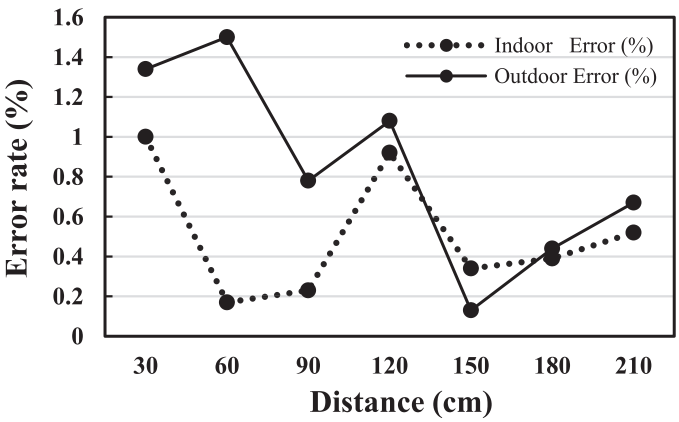


Fig. 10. Comparison of error rate between indoor and outdoor environment.

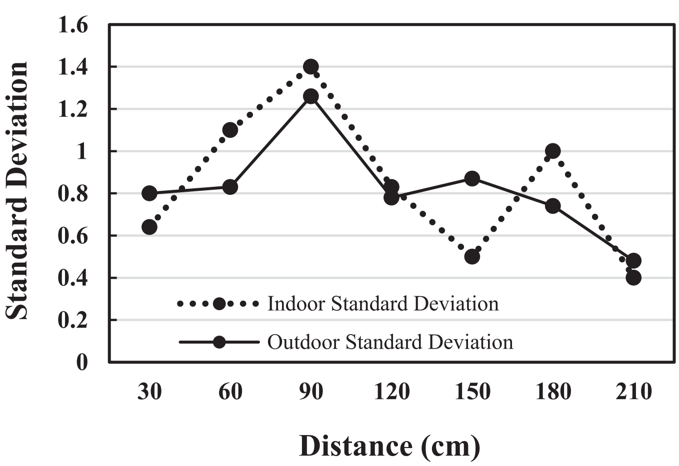


Fig. 11. Comparison of standard deviation between indoor and outdoor environment.

5 which is 0.50 of the indoor environment and 0.48 in region 7 of the outdoor environment.

In the theory of probability and statistics, the variance estimates how far a bunch of numbers is spread out. It is a mathematical value and is utilized to demonstrate how broadly individuals in a branch fluctuate. In the event that singular perceptions shift impressively from the group mean, the change is large and the other way around. The bigger value of the variance addresses the more data range in the general framework. It ought to be noticed that change is consistently non-negative- a little

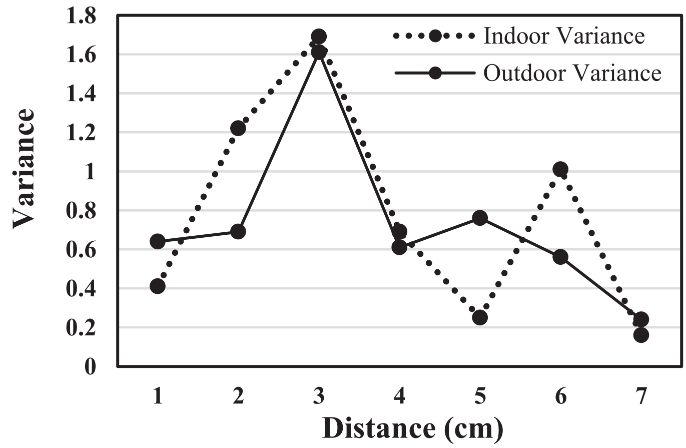


Fig. 12. Comparison of standard deviation between indoor and outdoor environment.

difference demonstrates that the points of data incline toward being near the mean and subsequently to one another while a high variance shows that the points of data are exceptionally spread out around the mean and from one another. The comparison of variance between the indoor and outdoor environment is illustrated in Fig. 12.

4.2. Object Recognition

The object recognition model was trained with the custom dataset in a GPU-enabled host computer for several object detection and currency note recognition to help the visually impaired people in the safe movement and daily transaction-related works. At the end of the training period, the model was transferred and implemented in Raspberry Pi which works as a single-board computer in the developed system. The object recognition experiment was done in both indoor and outdoor environments. The recognition module turns on automatically when an object is detected by the laser sensor and the distance is less than 150 cm. In both environments, we have checked 200 samples for each type of object. For each sample, we have calculated accuracy, error rate, precision, recall, and F1 score.

The performance of object recognition in the indoor environment is presented in Table 5. We have tested five different types of objects such as a person, staircase, chair, table, and washroom with eight currency notes. In the indoor environment, an average of 196 samples of objects is correctly recognized out of 200 samples. The average accuracy of object recognition is 98.11%. The highest accuracy is found to recognize the currency note of 100 taka is 100%. The developed system correctly identified 198 samples of that currency note and two samples were blank that means no currency note was taken in front of the spectacle and the system showed that there wasn't any currency note. So we took 198 samples as true positive and two blank samples as true negative in order to make a confusion matrix and calculate the performance measurement parameters. The lowest accuracy is found to recognize washroom and table in the indoor environment.

The performance of object recognition in the outdoor environment is depicted in Table 6. From table 6, it can be observed that an average of 197.61 samples of objects is correctly recognized by the developed system within 200 samples. We have made a confusion matrix to calculate the accuracy, precision, recall, and F1 score. In order to make a confusion matrix, we took correctly recognized the column as true positive, and other parameters of the matrix are varied from object to object. The average accuracy, precision, recall, and F1 score of object recognition in the outdoor environment is 98.76, 99.30, 99.57, and 99.43 respectively. The confusion matrix of several objects is illustrated in Fig. 13.

The accuracy of both environments is measured using the confusion matrix. The comparison of accuracy between that two environments is

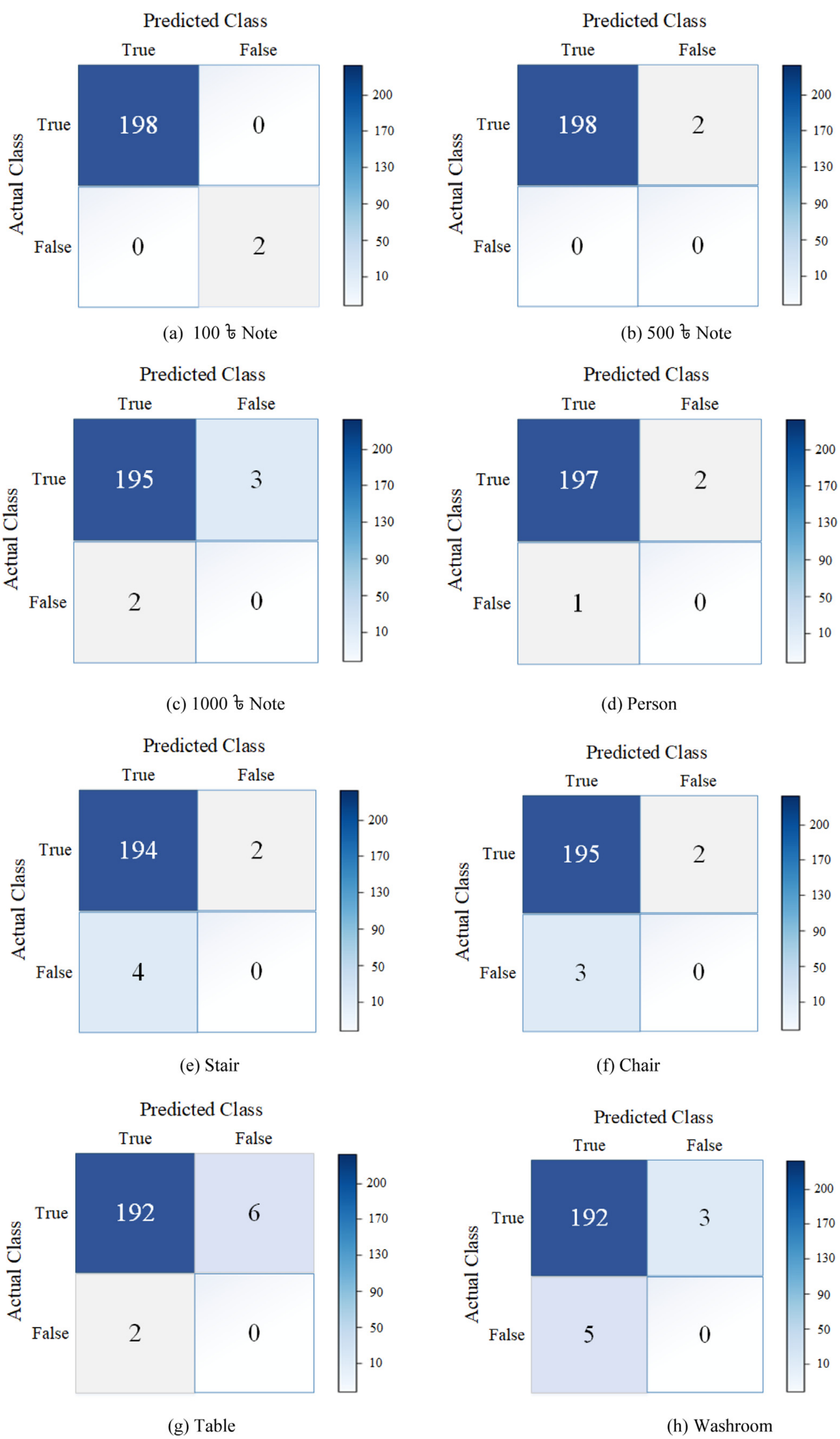


Fig. 13. Confusion matrices of several objects.

Table 5
Performance of object recognition in indoor environment.

Objects	Total Samples	Indoor					
		CorrectlyRecognized	Accuracy (%)	Error (%)	Precision	Recall	F1
5 Note	200	197	98.50	1.50	99.49	98.99	99.23
10 Note	200	198	99.00	1.00	99.49	99.49	99.49
20 Note	200	198	99.00	1.00	99.00	100.00	99.50
50 Note	200	197	98.50	1.50	99.49	98.99	99.23
100 Note	200	198	100.00	0.00	100.00	100.00	100.00
200 Note	200	196	98.00	3.50	98.49	99.49	98.98
500 Note	200	198	99.00	1.00	100.00	99.00	99.50
1000 Note	200	197	98.50	1.50	99.49	98.99	99.23
Person	200	195	97.50	2.50	98.98	98.48	98.73
Stairs	200	194	97.00	3.00	97.97	98.97	98.47
Chair	200	195	97.50	2.50	98.48	98.98	98.73
Table	200	192	96.00	4.00	98.96	96.96	97.95
Washroom	200	192	96.00	4.00	97.46	98.46	97.95

Table 6
Performance of object recognition in outdoor environment.

Objects	Total Samples	Outdoor					
		CorrectlyRecognized	Accuracy (%)	Error (%)	Precision	Recall	F1
5 Note	200	198	99.00	1.00	99.49	99.49	99.49
10 Note	200	198	99.00	1.00	99.00	100.00	99.50
20 Note	200	198	99.00	1.00	99.00	100.00	99.50
50 Note	200	199	99.50	0.50	100.00	99.50	99.74
100 Note	200	19/9	100.00	0.00	100.00	100.00	100.00
200 Note	200	198	99.00	1.00	99.49	99.49	99.49
500 Note	200	199	100.00	0.00	100.00	100.00	100.00
1000 Note	200	198	99.00	1.00	99.49	99.49	99.49
Person	200	198	99.00	1.00	99.00	100.00	99.50
Stairs	200	196	98.00	3.50	98.49	99.49	98.98
Chair	200	197	98.50	1.50	99.49	98.99	99.23
Table	200	195	97.50	2.50	98.98	98.48	98.73
Washroom	200	196	98.00	3.50	98.49	99.49	98.98

depicted in Tables 5 and 6. From the comparison, we can see that the average accuracy of the indoor and outdoor environment is 98.11% and 98.76% respectively. So the accuracy is obtained by the outdoor environment is seen as higher than the accuracy of the indoor environment. Overall the accuracy of object recognition of the developed system is 98.43%. The results imply that once the object is detected by the laser sensor and distance is less than 150 cm it will be recognized and categorized properly among the thirteen object classes that were pre-trained on a custom dataset.

Precision evaluates the quantity of positive class expectations that really have a place with the positive class. The precision is determined as the quantity of genuine positives divided by the all-out number of genuine positives and false positives. The precision of the outdoor environment is better than the precision of the indoor environment for all objects except the currency note 5 taka and 100 taka. The average precision of indoor and outdoor environments is 98.98% and 99.30% respectively.

Recall evaluates the quantity of positive class expectations made out of all positive models in the dataset. Dissimilar to the precision that only remarks on the right certain expectations out of every sure expectation, recall gives a sign of missed positive expectations. Thusly, recall gives some thought to the inclusion of the positive class. The comparison of precision of object recognition between indoor and outdoor environments is calculated from the data of Tables 5 and 6. From the comparison, we can see that in every case the recall of outdoor environment is better than the recall of indoor environment. The average value of recall in the indoor environment is 99.02% and the outdoor environment is 99.57% respectively.

F1-score provides a way to combine both precisions and recall into a single measure. That single score balances both the concerns of precision and recall in one number. From the comparison of the F1-score of object recognition between indoor and outdoor environments, it can be observed that the F1-score of the outdoor environment is higher than the F1-score of the indoor environment in all types of objects. The average F1-score of the indoor and outdoor environment is 98.98% and 99.43% respectively.

The ease of use and the degree of the solace of the developed prototype are estimated with the assistance of visually impaired people. There are 100 vision impaired persons, from Khulna Nesaria Madrasa, who have participated in this real-life survey. Among them, 65 people are completely blind, and 35 people are struggling with some degree of vision impairment. Initially, we have acquainted them with all aspects of the developed spectacle. We have taught them about the input signal that they would hear while walking, the location of the sensors, and how to use the spectacle. A set of few questions have been asked to get responses about the spectacle. The study is led in an open-air climate (outdoor) in sunshine conditions and the indoor environment of the madrasah.

5. Discussion

Several existing works tried to minimize the issues that are being faced by the visually impaired. Nearly all proposed systems are focused in limited directions. Some of them worked with only sensor-based systems [18–20] some worked with computer vision-based systems [21–23] and few other researchers worked on mobile platforms [24–26]. Nonetheless, detection range (i.e., near, intermediate, and far distances) for the users in real environments; feedback signals which are generated in the systems and passed to the users comfortably and safely, coverage area (indoor/outdoor), weight, cost, etc. concerning the vision impaired in low-income countries are somehow overlooked in most of the cases. Large gaps are remaining in the domain of reviewing the literature related to investigate the problems that visually impaired people are facing in real life.

Joshi et al. [27] proposed a Jetson Nano-based system in order to assist people who are vision impaired. The whole system employed Mobile Net, SSD, and Jetson Nano combined with the trained deep learning model and is connected with a camera, that functions as a get-at-able medium for various tasks such as object recognition, speech processing, and image classification. Instead of simply identifying the object, the system identifies the perceptible object and sends information to transmit facts about the object to the user through a headset. If an individual is completely in the frame but the distance is more, the accuracy level can be 94.8% where it would be 75.07% if the person is near but not in the frame entirely. However, the system is not IoT-enabled and the processing data does not save any database for further analysis. Furthermore, the system does not recognize the banknote in the real-time environment.

Afif et al. [28] put forth a recently entirely labeled dataset for indoor target exposure and identification which is related to visually impaired people's activity. The ingenuity of the suggested dataset turns up from the incorporation of new features of a 3D scene which is not deliberated so far and linked to visually impaired people's mobility. Such new training data will make the object recognition process more solid. The system proposed the first access evaluating YOLOv3 architecture on indoor target detection. However, the object detection rate is 73.19% which is very low and the system does not support outdoor object recognition. Joshi et al. [29] presented a smart navigation sharp system for vision-wakened people in which artificial intelligence is utilized. Along with the aid of different distance sensors, deep learning-based object detection is used to make the client informed about obstacles in order to contribute protected navigation where each and every message is supplied to the user through an audio signal. The presented system can distinguish between hindrances and known targets. A distance-estimating sensor is unified to prepare the device more extensively by identify obstacles while exploring different places. The suggested methodology can help vision weakened people. However, the average accuracy of the system for object detection is 95.19% which is not fast enough in the case of moving target detection.

Ayachi et al. [30] presented a computer vision system that is based on the RetinaNet that deals with the identification of specific indoor classes. Estimation is completed by utilizing different models like ResNet, DenseNet, and VGGNet in order to enhance identification capability and sort out the timing. The system was initiated and tested using indoor object detection and recognition dataset (IODR). The detection precision of the system is 84.61% mAP which is not satisfactory for visually impaired people. Noman et al. [31] suggested a system that identifies the hindrances looked at by vision-impaired people. The framework comprises a camera with a preparing unit and a Time-of-Flight sensor giving a proficient, advantageous, and practical accomplishment. The framework comes to a normal object recognition precision of 73.34% and a 5% error edge in identifying the distance and length of distinguished objects. However, the system is not IoT-enabled and the processing data does not save any database. Furthermore, the accuracy is very low and the system does not support outdoor object recognition. Yadav et al. [32] presented an assistive system for vision-impaired individuals to aid them with instinctive guidance and navigation. This system can identify the class of the object and can detect the hindrance at different levels such as chest, waist, knee, and foot level of the vision weakened person. It can also identify the soggy ground and audio acknowledgement is used to warn the users. The average detection accuracy of the device for obstacles is 94.00%. However, the device is not capable of identifying currency notes and also cannot store the processing data.

Bashiri et al. [33] proposed a system based on a deep neural network to guide visually impaired people in an unknown environment. However, the prototype is not able to identify currency and multiple objects at a time, and the acknowledgement procedure is still in the development stage. A navigation and object recognition system presented in [34] formed with a sensor and an IMU appended to a couple of glasses and a cell phone. Mala et al. [35] developed a navigation gadget based on IoT for sightless people. The system used the Global Positioning System to track the current position of the vision loss people. However, this gadget can detect only obstacles but it cannot identify the type of obstacle.

Murad et al. [10] proposed a MobileNet-based CNN to recognize Bangla Banknote. The paper contributed a vast novel dataset of 8000 images of Bangladeshi banknotes. For the classification of banknotes, they used MobileNet deep learning architecture. Tasnim et al. [36] presented a real-time Bangladeshi-banknote recognition scheme using CNN for visually impaired people. A new dataset has been created consisting of more than 70,000 images of currently available Bangladeshi banknotes. The system can identify the eight banknotes used in Bangladesh with an average accuracy of 92% and exhibit the result with both textual and auditory output. Jahangir et al. [37] proposed an automated banknote recognition system based on the neural network using axis symmetrical masks to aid visually impaired people. This system can recognize currently running 8 banknotes successfully and the average accuracy is 98.57%.

Choudhary et al. [38] developed an IoT-based system that aids visually impaired people to access public transport. The system was constructed with two different modules, a user module, and a bus module. The system uses GPS to track the bus stand. In order to exchange information, the system needs to connect to a wireless network. Ali J. Ramadhan [39] suggested a smart system that is wearable, to ensure the independent and protected mobility of visually impaired persons. An ATmega328 microcontroller embedded with an Arduino Uno with various types of sensors is included in it. An HC-SR04 ultrasonic sensor is used to identify obstacles, an ADXL345 accelerometer is used to detect the fall of the user, and GSM and GPS modules are used to trace the location of the user. Different types of features are included in it such as lower body part obstacle detection and localization and communication in emergency situations. Morad [40] designed a localization-based system to help sightless in safe navigation. It contains a GPS receiver, microcontroller, microphone, and headset. The GPS receiver is used to find the position of the user and an LCD is used to read the current position coordinates by the designer. However, the system does not have the feature of obstacle detection.

Rahman et al. [41] proposed a wearable electronic system to detect obstacles and falls of visually impaired people. The system consists of some sensors, an android application, and a data transmission module. The accuracy of the system is 98.34%. However, the system is not capable of identifying the class of the detected object. KAVYA et al. [42] presented a vision-based fall detection system in the real-time scenario by investigating the pace of progress of movement as for the ground point. An individual's movement is followed by utilizing a Kalman channel and calculates the point between the followed focuses as for a ground point. For trial investigation, the framework utilized two public datasets and examined boundaries. Chang et al. [43] designed an intelligent assistive device that is consists of wearable glasses and a stick for outwardly impaired individuals in object detection and fall recognition. Vision impaired people are guided by the vibrating walking stick to avoid collision and accidents. Furthermore, when visually impaired people fall, an alarming acknowledgement is sent without any delay to their guardians. The average accuracy of fall detection is 98.3%.

The comparison of the performance among the proposed system and some existing systems is shown in Table 7. We have chosen several parameters like Coverage area, Detection range, Weight, Cost, Dataset, Connection type, accuracy, and status, etc. in order to complete the comparison table. From Table 7, it can be seen that most of the existing systems covered both indoor and outdoor environments except [44,45], and [23]. The object detection range of the proposed system is

Table 7
Performance analysis of the proposed system in comparison to existing systems.

Authors	Coverage area	Detection range	Weight	Cost	Dataset	Connection	Accuracy	Object	
								Detection	Recognition
[44]	Indoor	0.05 m - 3.5m	High weight	Low	N/A	Offline	N/A	✔	✖
[22]	Indoor & outdoor	N/A	A few hundred of grams	High	Local Dataset	Offline	94.87%	✔	✔
[45]	Indoor	2m-4m	170 g	High	N/A	Offline	N/A	✔	✖
[24]	Indoor & outdoor	0m-3.5m	A few hundred of grams	Low	Local Dataset	Offline	95.19%	✔	✔
[46]	Indoor & outdoor	0.09m- 0.20 m	Bulky but wearable	High	N/A	Offline	N/A	✔	✖
[36]	Indoor & outdoor	0m-3.5m	A few hundred of grams	Low	N/A	Online	98.34%	✔	✖
[29]	Indoor & outdoor	N/A	Bulky	High	MS COCO	Offline/Online	N/A	✔	✔
[23]	Indoor	N/A	Bulky	High	COCO	Offline	N/A	✔	✔
Proposed System	Indoor & outdoor	0.02m-4m	A few hundred of grams	Low	Custom dataset	Online	98.43%	✔	✔

Not Mentioned: N/A.

higher than all other mentioned systems which are 0.01m-4 m. The system proposed in [45], had covered 4 m distance but it started from 2 m. Most of those existing systems had high weight. Though the systems of [22] and [45] had low weight, their cost was high. The proposed system has maintained both low cost and low weight. Almost all the existing systems working procedure was offline-based. The system of [29] had both offline and online-based functionalities but the accuracy was unknown. The system of [36] is online-based but its accuracy is slightly lower than the proposed system which is 98.34%. All the existing systems can detect objects, but several of them have object recognition functionality. In this case, our proposed system has both object detection and recognition module with high accuracy of 98.43% based on a custom dataset.

6. Conclusions

This paper has proposed an IoT-enabled automated system that can help visually impaired in their safe navigation and identifies several common objects in indoor and outdoor environments in real-time scenarios. The currency notes, currently used in Bangladesh, can also be recognized by the proposed system. The objects are detected by laser sensors in the direction of the front, left, right, and ground. The Single-Shot-Detector is used to recognize objects and an audio signal is provided by the system to aware the user using the headphone through Bluetooth technology. The pre-trained model is prepared on a host computer using two custom datasets that are created manually. Overall, the system can detect all types and shapes of objects but can recognize five different types of objects and eight currency notes. The object detection and recognition accuracy of the developed system is 99.31% and 98.43% respectively. The developed system can send a warning notification to others (friends, relatives, etc.) in case a true free fall has been occurred. All processed data and information regarding objects' recognition are sent and stored to a remote server in real-time to ensure the safety of the users and for further analysis by the researchers.

At present, the weight of the system is a few hundred grams and all the components are connected by wires that have increased the size of the system. Also, the system can recognize five different types of objects with eight currency notes. The future enhancements of the proposed method may focus on the development of a system-on-chip (SoC) so that the size, weight, and cost of the system can be reduced. Moreover, new methodology could be introduced to increase the number of objects to be recognized.

References

[1] R.R. Bourne, et al., Magnitude, temporal trends, and projections of the global prevalence of blindness and distance and near vision impairment: a systematic review and meta-analysis, Lancet Global Health 5 (9) (2017) 888–897.
[2] Q. Lu, "Feasibility study of a" smart" aid for the visually impaired and blind's independent mobility in outdoor environments," ed, 2018.
[3] J. Hong, H. Yi, J. Pyun, W. Lee, SoundWear: effect of non-speech sound augmentation on the outdoor play experience of children, in: Proceedings of the 2020 ACM Designing Interactive Systems Conference, 2020, pp. 2201–2213.
[4] E. Cardillo, et al., An electromagnetic sensor prototype to assist visually impaired and blind people in autonomous walking, IEEE Sens. J. 18 (6) (2018) 2568–2576.
[5] R.S. Mulky, S. Koganti, S. Shahi, K. Liu, Autonomous scooter navigation for people with mobility challenges, in: 2018 IEEE International Conference on Cognitive Computing (ICCC), IEEE, 2018, pp. 87–90.
[6] L. Mesquita, J. Sánchez, R.M. Andrade, Cognitive impact evaluation of multimodal interfaces for blind people: towards a systematic review, in: International Conference on Universal Access in Human-Computer Interaction, Springer, 2018, pp. 365–384.
[7] J. Chehade, G. Abou Haydar, A. Hayek, J. Boercsoek, J.J.S. Olmedo, Design and implementation of smart shoes for blind and visually impaired people for more secure movements, in: 2020 32nd International Conference on Microelectronics (ICM), IEEE, 2020, pp. 1–6.
[8] Q. Zhang, W.Q. Yan, M. Kankanhalli, Overview of currency recognition using deep learning, J. Bank. Financ. Technol. 3 (1) (2019) 59–69.
[9] V. Veeramsetty, G. Singal, T. Badal, Coinnet: platform independent application to recognize Indian currency notes using deep learning techniques, Multimed. Tools Appl. 79 (2020) 22569–22594.
[10] H. Murad, N.I. Tripto, M.E. Ali, Developing a bangla currency recognizer for visually impaired people, in: Proceedings of the Tenth International Conference on Information and Communication Technologies and Development, 2019, pp. 1–5.
[11] A. Habib, M.M. Islam, M.N. Kabir, M.B. Mredul, M. Hasan, Staircase detection to guide visually impaired people: a hybrid approach, Revue d'Intelligence Artificielle 33 (5) (2019) 327–334.
[12] S. Ponnada, S. Yarramalle, M.R. TV, A hybrid approach for identification of manhole and staircase to assist visually challenged, IEEE Access 6 (2018) 41013–41022.
[13] Y. Li, H. Huang, Q. Xie, L. Yao, Q. Chen, Research on a surface defect detection algorithm based on MobileNet-SSD, Appl. Sci. 8 (9) (2018) 1678.
[14] T.-.Y. Lin, et al., Microsoft coco: common objects in context, in: European conference on computer vision, Springer, 2014, pp. 740–755.
[15] J. Singh, B. Bhushan, Real time indian license plate detection using deep neural networks and optical character recognition using LSTM tesseract, in: 2019 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), IEEE, 2019, pp. 347–352.
[16] W. Liu, et al., Ssd: single shot multibox detector, in: European conference on computer vision, Springer, 2016, pp. 21–37.
[17] D.G. Lowe, Object recognition from local scale-invariant features, in: Proceedings of the seventh IEEE international conference on computer vision, 2, Ieee, 1999, pp. 1150–1157.
[18] G. Farias, et al., A neural network approach for building an obstacle detection model by fusion of proximity sensors data, sensors 18 (3) (2018) 683.
[19] O. Arslan, D.E. Koditschek, Sensor-based reactive navigation in unknown convex sphere worlds, Int. J. Rob. Res. 38 (2–3) (2019) 196–223.
[20] H. Liu, J. Ma, W. Huang, Sensor-based complete coverage path planning in dynamic environment for cleaning robot, CAAI Trans. Intell. Technol. 3 (1) (2018) 65–72.

[21] R. Fang, C. Cai, Computer vision based obstacle detection and target tracking for autonomous vehicles, in: MATEC Web of Conferences, 336, EDP Sciences, 2021, p. 07004.
[22] S.-.H. Wang, X.-.X. Li, A real-time monocular vision-based obstacle detection, in: 2020 6th International Conference on Control, Automation and Robotics (ICCAR), IEEE, 2020, pp. 695–699.
[23] Z. Zhang, Y. Cao, M. Ding, L. Zhuang, J. Tao, Monocular vision based obstacle avoidance trajectory planning for Unmanned Aerial Vehicle, Aerosp. Sci. Technol. 106 (2020) 106199.
[24] N. Pavliuk, I. Kharkov, E. Zimuldinov, V. Saprychev, Development of multipurpose mobile platform with a modular structure, in: Proceedings of 14th International Conference on Electromechanics and Robotics "Zavalishin's Readings, Springer, 2020, pp. 137–147.
[25] E. Aksamentov, K. Zakharov, D. Tolopilo, E. Usina, Approach to robotic mobile platform path planning upon analysis of aerial imaging data, in: Proceedings of 15th International Conference on Electromechanics and Robotics" Zavalishin's Readings", Springer, 2021, pp. 93–103.
[26] W. Chen, Q. Liu, H. Hu, J. Liu, S. Wang, Q. Zhu, Novel laser-based obstacle detection for autonomous robots on unstructured terrain, Sensors 20 (18) (2020) 5048.
[27] R. Joshi, M. Tripathi, A. Kumar, M.S. Gaur, Object recognition and classification system for visually impaired, in: 2020 International Conference on Communication and Signal Processing (ICCSP), IEEE, 2020, pp. 1568–1572.
[28] M. Afif, R. Ayachi, E. Pissaloux, Y. Said, M. Atri, Indoor objects detection and recognition for an ICT mobility assistance of visually impaired people, Multimed. Tools Appl. 79 (41) (2020) 31645–31662.
[29] R.C. Joshi, S. Yadav, M.K. Dutta, C.M. Travieso-Gonzalez, Efficient multi-object detection and smart navigation using artificial intelligence for visually impaired people, Entropy 22 (9) (2020) 941.
[30] M. Afif, R. Ayachi, Y. Said, E. Pissaloux, M. Atri, An evaluation of retinanet on indoor object detection for blind and visually impaired persons assistance navigation, Neural Proc. Lett. (2020) 1–15.
[31] M. Noman, V. Stankovic, A. Tawfik, Portable offline indoor object recognition system for the visually impaired, Cogent Eng. 7 (1) (2020) 1823158.
[32] S. Yadav, R.C. Joshi, M.K. Dutta, M. Kiac, P. Sikora, Fusion of object recognition and obstacle detection approach for assisting visually challenged person, in: 2020 43rd International Conference on Telecommunications and Signal Processing (TSP), IEEE, 2020, pp. 537–540.
[33] F.S. Bashiri, E. LaRose, J.C. Badger, R.M. D'Souza, Z. Yu, P. Peissig, Object detection to assist visually impaired people: a deep neural network adventure, in: International Symposium on Visual Computing, Springer, 2018, pp. 500–510.
[34] J. Bai, Z. Liu, Y. Lin, Y. Li, S. Lian, D. Liu, Wearable travel aid for environment perception and navigation of visually impaired people, Electronics (Basel) 8 (6) (2019) 697.
[35] N.S. Mala, S.S. Thushara, S. Subbiah, Navigation gadget for visually impaired based on IoT, in: 2017 2nd International Conference on Computing and Communications Technologies (ICCCT, IEEE, 2017, pp. 334–338.
[36] R. Tasnim, S.T. Pritha, A. Das, A. Dey, Bangladeshi banknote recognition in real–time using convolutional neural network for visually impaired people, in: 2021 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST), IEEE, 2021, pp. 388–393.
[37] N. Jahangir, A.R. Chowdhury, Bangladeshi banknote recognition by neural network with axis symmetrical masks, in: 2007 10th international conference on computer and information technology, IEEE, 2007, pp. 1–5.
[38] S. Choudhary, V. Bhatia, K. Ramkumar, IoT based navigation system for visually impaired people, in: 2020 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO), IEEE, 2020, pp. 521–525.
[39] A.J. Ramadhan, Wearable smart system for visually impaired people, Sensors 18 (3) (2018) 843.
[40] A.H. Morad, GPS talking for blind people, J. Emerg. Technol. Web Intell. 2 (3) (2010) 239–243.
[41] M.M. Rahman, M.M. Islam, S. Ahmmed, S.A. Khan, Obstacle and fall detection to guide the visually impaired people with real time monitoring, SN Comput. Sci. 1 (2020) 1–10.
[42] T.S. Kavya, Y.-.M. Jang, E. Tsogtbaatar, S.-.B. Cho, Fall detection system for elderly people using vision-based analysis, Sci. Technol. 23 (1) (2020) 69–83.
[43] W.-.J. Chang, L.-.B. Chen, M.-.C. Chen, J.-.P. Su, C.-.Y. Sie, C.-.H. Yang, Design and implementation of an intelligent assistive system for visually impaired people for aerial obstacle avoidance and fall detection, IEEE Sens J 20 (17) (2020) 10199–10210.
[44] S. Sharma, M. Gupta, A. Kumar, M. Tripathi, M.S. Gaur, Multiple distance sensors based smart stick for visually impaired people, in: 2017 IEEE 7th Annual Computing and Communication Workshop and Conference (CCWC), IEEE, 2017, pp. 1–5.
[45] C. Ton, et al., LIDAR Assist spatial sensing for the visually impaired and performance analysis, IEEE Trans. Neural Syst. Rehabil. Eng. 26 (9) (2018) 1727–1734.
[46] S.T.H. Rizvi, M.J. Asif, H. Ashfaq, Visual impairment aid using haptic and sound feedback, in: 2017 International Conference on Communication, Computing and Digital Systems (C-CODE), IEEE, 2017, pp. 175–178.
[47] D.-M. Lee, "Single Shot Multibox Detector - Real-time character recognition for Windows through Inference Program Development," 2018.