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Stochastic Gradient Descent with Deep Learning-assisted Object Detection and Classification for Visually Challenged People

Nabil Almalki[1,2,*], Mrim M. Alnfiai[2,3], Fahd N. Al-Wesabi[4], Mesfer Alduhayyem[5], Anwer Mustafa Hilal[6] and Manar Ahmed Hamza[6]

[1]Department of Special Education, College of Education, King Saud University, Riyadh 12372, Saudi Arabia
[2]King Salman Center for Disability Research, Riyadh, Saudi Arabia
[3]Department of Information Technology, College of Computers and Information Technology, Taif University, Taif 21944, Saudi Arabia
[4]Department of Computer Science, College of Science and Arts, King Khaled University, Saudi Arabia
[5]Department of Computer Science, College of Sciences and Humanities—Aflaj, Prince Sattam Bin Abdulaziz University, Saudi Arabia
[6]Department of Computer and Self Development, Preparatory Year Deanship, Prince Sattam Bin Abdulaziz University, AlKharj, Saudi Arabia

Correspondence to:
Nabil Almalki*, e-mail: nalmalki@ksu.edu.sa

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ABSTRACT

Object detection and classification systems can be devised to support visually challenged persons in communicating and understanding their environments. Such systems use computer vision methods for classifying and detecting objects in real time. Deep learning (DL) can be adopted to help visually challenged persons in object classification and detection tasks, allowing them to communicate and understand their surroundings more efficiently. By leveraging DL for object detection and classification, visually challenged individuals can receive real-time data regarding their interaction, surroundings, and overall independence and facilitate their navigation. With this motivation, the study presents a novel Stochastic Gradient Descent with Deep Learning-assisted Object Detection and Classification (SGDDL-ODC) technique for visually challenged people. The main intention of the SGDDL-ODC technique concentrates on the accurate and automated detection of objects to help visually challenged people. To obtain this, the SGDDL-ODC technique focused on the development of the optimal hyperparameter tuning of the DL models effectively. To accomplish this, the SGDDL-ODC technique follows the YOLOv6 model for object detection purposes. To adjust the hyperparameter values of the YOLOv6 method, the SGD model can be applied. At the final stage, the deep neural network method can be exploited for the classification of the recognized objects. A series of simulations were performed to validate the improved performance of the SGDDL-ODC approach. The simulation results illustrate the superior efficiency of the SGDDL-ODC technique over other techniques under diverse datasets in terms of different measures.

KEYWORDS

visually impaired people, deep learning, computer vision, object detection, stochastic gradient descent

INTRODUCTION

The life of an individual relies on the fundamental five senses where the capability of vision becomes the most significant factor. Visual impairment refers to a reduced capability to see something to a level that the eye cannot see even utilizing usual means, like glasses or lenses (Nagarajan and Gopinath, 2023). Visually impaired persons (VIPs) lack the sense of vision. Therefore, performing the everyday tasks of life is difficult for those people (Joshi et al., 2020). This may result in problems that can be subdued momentarily by few supporting personnel, and a case exists where few circumstances may be fatal (Abdul-Ameer et al., 2022). With the advances, several research studies were presented that specified the design of gadgets for VIPs. Such gadgets were durable and simple, but they were deficient in accuracy and usage. Since the modern world depends on artificial intelligence and computers, such methods have become more efficient and reliable (Abdusalomov et al., 2022). Still, numerous gaps exist in these technologies. In this study, embedded systems, RFID sensors, and Logitech cameras are employed to devise a potential system.

In the past, various approaches, systems, devices, and applications were advanced in the assistive technology domain for facilitating VIPs to perform tasks that they were formerly incapable of doing (Vaidya et al., 2020). These solutions have electronic gadgets equipped with microprocessors, cameras, and sensors proficient in taking choices and offering auditory or tactile responses to the user (Bhalekar and Bedekar, 2022). Several prevailing object recognition and detection systems claim higher precision but cannot offer essential data and attributes for chasing VIPs to safeguard their safe mobility. Although disabled persons cannot see objects in their environments, it is useful to know about them (Srinivasan et al., 2020). Moreover, it is necessary to devise a method whereby the relations of the VIPs could observe their activities. Considering the abovementioned requirement, this study proposes a clever system that implements object recognition and localization (Busaeed et al., 2022). Once the scheme identifies the object, it transmits audio feedback to the user. For instance, after recognizing the car (object), the user hears the word "car." Furthermore, the location of the user and a picture of the currently watched act are sometimes saved in a server that is evaluated by the family members through the application for tracking the user (Aralikatti et al., 2020). For object recognition and detection, the MobileNet model can be exploited due to its lower computation difficulty to proceed with low devices' end power. Meanwhile, wearable hardware and resource was constrained, and the feedback system regarding the object's name should be as close as possible; complicated object detection methods might not be as feasible as the initial technique (Choi et al., 2019).

In Sultana (2023), devised STFT empirical and EMD are exploited to abstract features as spatio-temporal data from the EEG signal. In this study, the signal can be disintegrated into intrinsic mode function denoting the number of signals in the maintenance of the time domain and STFT was employed to renovate time to time-frequency domains. In unfamiliar indoor environments, SVM was implemented for classifying the VIP stress. Patel et al. (2018) presented a multisensor-related mechanism for object detection in an indoor atmosphere. Using statistical parameters, object detection can be performed on captured images that can be validated with the use of the SVM method. The multi-sensor concept is used by interfacing ultrasonic sensors. Furthermore, to increase the precision of object detection, using an infrared sensor, small objects near feet can be identified.

Shah et al. (2021) devised the ideology of utilizing object recognition to aid VIPs. In this study, an experiment was presented that utilizes custom-built image data of different hazardous objects. The objects were classified into manhole, sharp objects, broken glass, fires, and danger signs. Many methods were trained on this custom image data covering the menacing object and the performance was assessed. Elmannai and Elleithy (2018) presented an intellectual structure to support VIPs. The presented work integrated sensor-related and computer vision-related techniques to offer a precise and economical solution. Such approaches allow us to find many objects and improve the precision of the collision avoidance structure. Additionally, based on the fuzzy logic and image depth information, the author presented a new obstacle avoidance method. Utilizing the FL, we were able to offer precise data to help the VI user in evading front obstacles.

The objective of Kamble et al. (2018) was object identification with advanced methods like deep learning (DL) on handy gadgets like tablets and smartphones. DL methods and CNN were utilized for object detection. Images are clicked using the smartphone camera in investigation and are given to the CNN model. In Kim et al. (2022), the annotation of the SMD data was corrected and an improved version was presented that coined SMD-Plus for a benchmark of deep neural network (DNN) methods. Vijlyakumar et al. (2020) intended to offer navigation to those people. It guides the people regarding the object along with offering the distance of the objects. The method computes the object distance. Here it offers the audio jack for insisting them about objects.

This study presents a new Stochastic Gradient Descent with Deep Learning-assisted Object Detection and Classification (SGDDL-ODC) technique for visually challenged people. The main intention of the SGDDL-ODC technique concentrates on the accurate and automated detection of objects to help visually challenged people. To obtain this, the SGDDL-ODC technique focused on the development of the optimal hyperparameter tuning of the DL models effectively. To accomplish this, the SGDDL-ODC technique follows the YOLOv6 model for object detection purposes. To adjust the hyperparameter values of the YOLOv6 model, the SGD model can be applied. At the final stage, the DNN method can be exploited for the classification of the recognized objects. A series of simulations were performed to validate the improved performance of the SGDDL-ODC technique.

THE PROPOSED OBJECT DETECTION MODEL

This study has presented a new SGDDL-ODC technique to detect and classify objects for visually challenged people. The main intention of the SGDDL-ODC technique concentrates on the accurate and automated detection of objects to help visually challenged people. To obtain this, the SGDDL-ODC technique focused on the development of the optimum hyperparameter tuning of the DL models effectively. To accomplish this, the SGDDL-ODC technique comprises a YOLOv6 object detector, a DNN classifier, and SGD-based optimum parameter tuning. Figure 1 depicts the workflow of the SGDDL-ODC approach.

Object detection module

Initially, the SGDDL-ODC technique follows the YOLOv6 model for object detection purposes. YOLOv6 is the new object detection technique and a single-stage object detection framework, which exploits a single pass over the network to implement recognition and classification of objects, making YOLOv6 more efficient and faster than a multi-phase object detection framework (Bist et al., 2023). YOLOv6-PB is a complex NN model comprising different parts, all of which play a certain role in object detection. A few major parts of YOLOv6-PB are given below:

The pretrained PB image dataset was fed into the model to predict the input part of YOLOv6-PB. The input image sizes rely on the proposed model; however, it is predicted to be a fixed size, for instance, 640×640×3 pixels as the default size.

The backbone extracts features from the input PB images. The backbone network in YOLOv6-PB is usually a pretrained

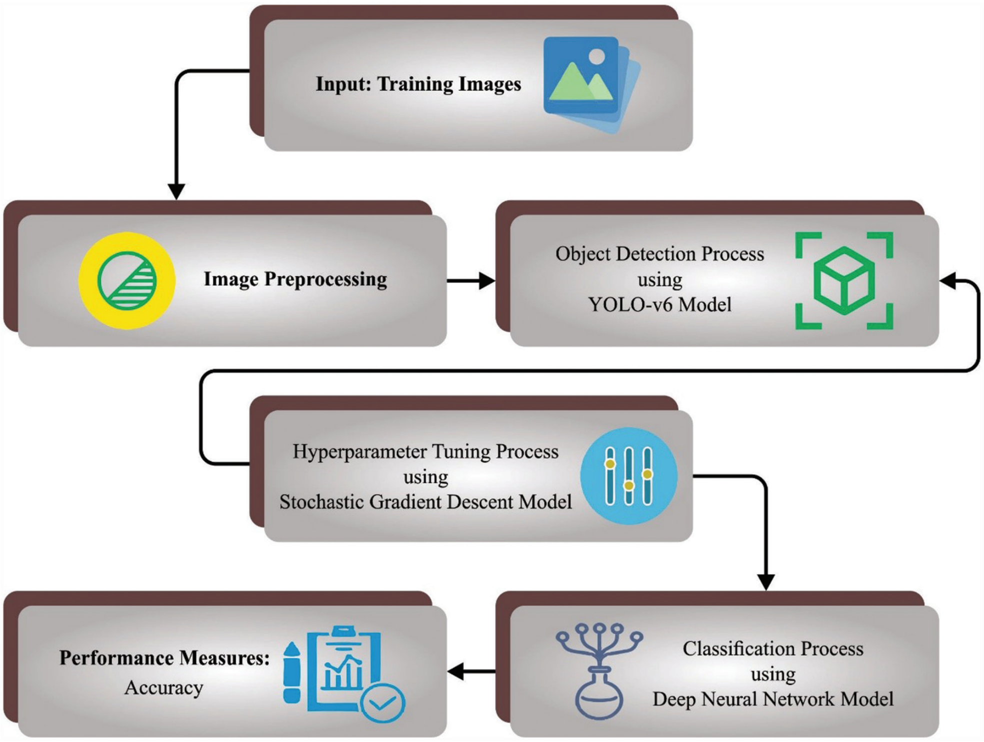

Figure 1: Workflow of the SGDDL-ODC approach. Abbreviation: SGDDL-ODC, Stochastic Gradient Descent with Deep Learning-assisted Object Detection and Classification.

CNN that was fine-tuned for object recognition. The structure of the backbone network in YOLOv6-PB might differ; however, it usually comprises multiple convolution layers, and max-pooling layers that assist in decreasing the spatial dimension of the feature map. The convolutional layer detects lower-level features in the PB images namely textures and edges. Spatial pyramid pooling assists the max-pooling layer in minimizing the size of the feature map and preserving the crucial feature for object recognition. Likewise, the EfficientRep Backbone applied in YOLOv6-PB can be developed to efficiently utilize the computation resource of hardware namely the GPU, and have stronger feature representation capabilities than the CSP-Backbone exploited by YOLOv5.

The neck connects backbone networks to the remaining system which considers the PB output of the backbone system and implements further processing to generate the last feature map utilized for PB object recognition. Generally, the proposed model aims to give an intermediate feature map relevant for the head to make precise predictions. Feather map was frequently attained by a sequence of up-sampling, convolutional, and pooling layers and manipulates the feature from the backbone network to the desirable scale and resolution for the head.

The anchor box is a predetermined bounding box that denotes the PB object in the images. It offers priori data regarding the size and location of PB objects in the images. The network learns to alter the anchor box to fit the PB objects.

The detection head was accountable for predicting the PB object in the images. It considered the neck network output and produced a group of bounding boxes and class possibilities for all target PB objects in the images. The recognition head makes use of an anchor box as the initial point and alters it to apt the PB object in an image. The proposed model shortening the head design, leverages a decoupled head structure while matching the representation abilities of the related operation with the computing difficulties on the hardware.

The loss function trained the network by calculating the variance among the forecasts made by the ground truth annotations and the network. The error between the ground truth class labels of *PB* and forecasted class probabilities and the loss function measured the error among the forecasted ground truth and bounding boxes.

$$Loss = \lambda_1 L_{cls} + \lambda_2 L_{obj} + \lambda_3 L_{loc} \quad (1)$$

In Equation (1), L_{cls}, L_{obj}, and L_{loc} exemplify class loss, PB object loss, and bounding box loss or location, correspondingly, and λ is constant for corresponding loss.

Hyperparameter tuning module

To adjust the hyperparameter values of the YOLOv6 method, the SGD model can be applied. SGD and its variants are utilized for DL (Yaqub et al., 2020). Such methods have definite steps that yield outputs by considering inputs for producing exact outcomes. As per target work and cost work, the optimal methods can be ascertained by neural networks, strategic relapse, and linear regression. The proposed method aims to limit the computation cost. The SGD-related method enables users to customize the system measures for a huge dataset:

$$W = \omega - \eta \nabla Q_i(\omega), \tag{2}$$

where $Q_i(\omega)$ indicates the predicted data, with $-Q_i$ being present data under observation. Mostly, Q denotes an error function; consequently, by tracking gradient direction in space of values of (ω), we move toward the direction of (ω) which minimizes the error SGD computed the best (ω) by diminishing Q concurrently prominently, with either linear regression or perception segmentation or (ω) necessitates the model's weight parameters and $Q(\omega)$ signifies the error for the method. Regular GD is given below:

$$W \leftarrow \eta \nabla Q(\omega). \tag{3}$$

In Equation (3), the error objective is (with its gradient)

$$Q(\omega) = ln \sum iQi(\omega) \Rightarrow \nabla Q(\omega) = ln \sum i \nabla Qi(\omega). \tag{4}$$

Object classification module

Finally, the DNN model can be exploited for the classification of the recognized objects. An artificial neural network can be described as "a computing system comprised of many simple, highly interconnected processing elements which process data by their dynamic state response to external input" (Thanki, 2023). FFNN is exploited in applications like person recognition, data prediction, and big data analysis. This model primarily comprises input, hidden, and output layers.

Figure 2 defines the architecture of DNN. The amount of nodes or neurons depends on the size of the input and output. All the nodes are fully connected to their neighboring layer and are interconnected by the link resounding specific weight. The NN is capable of learning weights for unstructured datasets including videos and images. Thus, activation functions like ReLU and sigmoid functions are leveraged with the NN. The bias was utilized to shift the activation function for best data prediction.

$$y = p + b \tag{5}$$

$$p = W_1 \times x_1 + W_2 \times x_2 + \ldots + W_N \times x_N, \tag{6}$$

where b is a bias, y shows the predicted output value, W represents the weight value of all the nodes, and x is the input value.

DNN was an extension of NN. DNN comprises multiple hidden layers (HLs), an input layer, and an output layer. Now, nodes interconnect all the layers where all the HLs provide predicted outcomes based on the prediction of the prior layer. The major difference between DNN and NN is that NN has a single HL while DNN has multiple HLs.

RESULTS AND DISCUSSION

This section offers detailed object detection and classification outcomes of the SGDDL-ODC method. In Table 1 and Figure 3, the obstacle detection outcomes of the SGDDL-ODC method are compared with the DeepNavi approach (Kuriakose et al., 2023). The results indicate that the SGDDL-ODC technique gained increased $accu_y$ under all classes. For example, on the bench class, the SGDDL-ODC technique attains a higher $accu_y$ of 96.58% while the DeepNavi model obtains a lower $accu_y$ of 93.70%. Also,

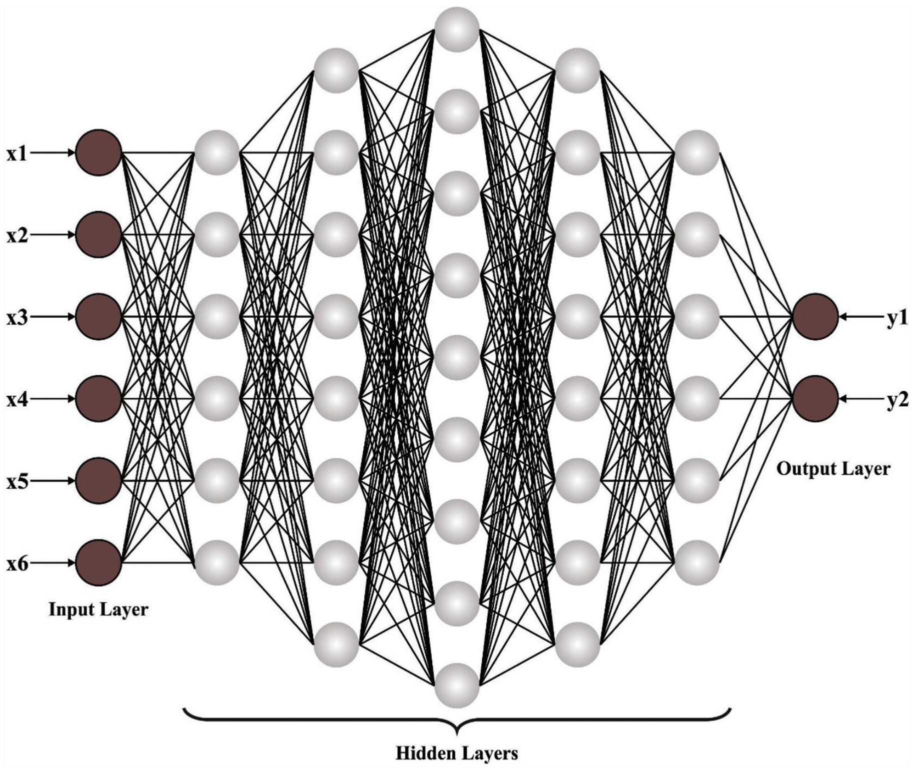

Figure 2: The DNN architecture. DNN, deep neural network.

Table 1: *Accu$_y$* analysis of the SGDDL-ODC approach with other methods under obstacle detection dataset.

Obstacle detection Class	DeepNavi	SGDDL-ODC
Bench	93.70	96.56
Bicycle	88.50	95.78
Billboard	84.60	96.30
Bookcase	90.20	95.76
Car	92.10	95.49
Chair	94.70	96.58

Abbreviation: SGDDL-ODC, Stochastic Gradient Descent with Deep Learning-assisted Object Detection and Classification.

in the bicycle class, the SGDDL-ODC method reaches a higher $accu_y$ of 95.78% while the DeepNavi method gains a lower $accu_y$ of 88.50%. In addition, on the billboard class, the SGDDL-ODC algorithm attains a higher $accu_y$ of 96.30% while the DeepNavi method obtains a lower $accu_y$ of 84.60%.

Meanwhile, in the bookcase class, the SGDDL-ODC algorithm attains a higher $accu_y$ of 95.76% while the DeepNavi technique obtains a lower $accu_y$ of 90.20%. Eventually, on the car class, the SGDDL-ODC technique gains a higher $accu_y$ of 95.49% while the DeepNavi method has a lower $accu_y$ of 92.10%. Finally, on the chair class, the SGDDL-ODC technique attains a higher $accu_y$ of 94.70% while the DeepNavi method acquires a lower $accu_y$ of 94.70%.

Figure 4 inspects the accuracy of the SGDDL-ODC method in the training and validation of the obstacle detection database. The result highlighted that the SGDDL-ODC technique has higher accuracy values over greater epochs. In addition, the higher validation accuracy over training

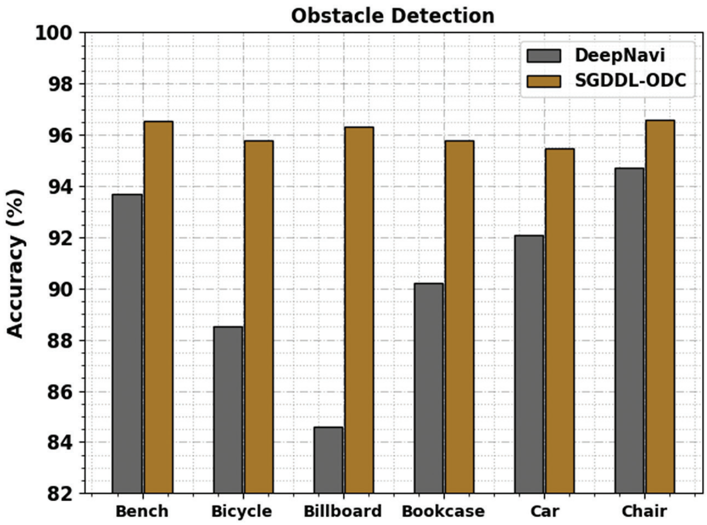

Figure 3: *Accu$_y$* analysis of the SGDDL-ODC approach under obstacle detection dataset. Abbreviation: SGDDL-ODC, Stochastic Gradient Descent with Deep Learning-assisted Object Detection and Classification.

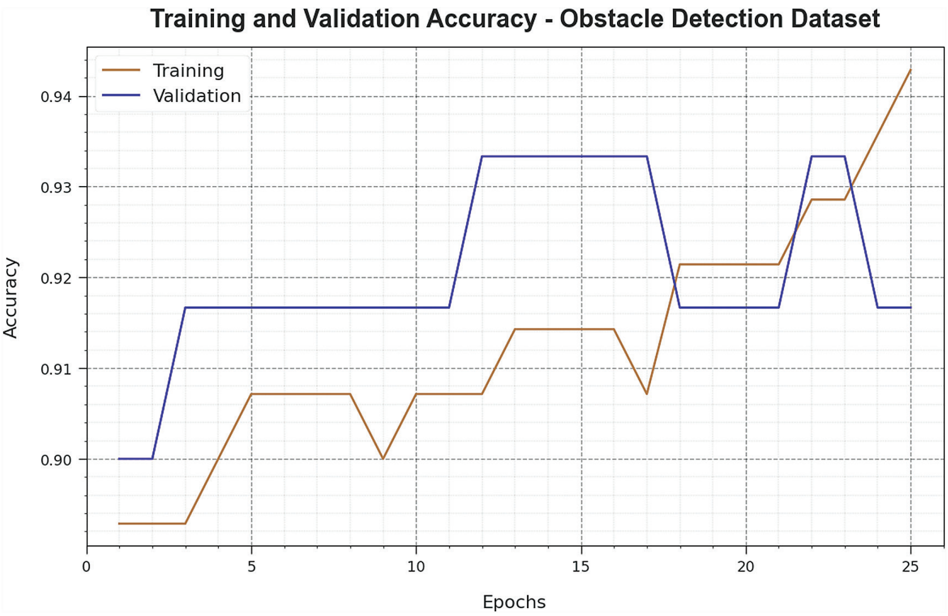

Figure 4: Accuracy curve of the SGDDL-ODC approach under obstacle detection dataset. Abbreviation: SGDDL-ODC, Stochastic Gradient Descent with Deep Learning-assisted Object Detection and Classification.

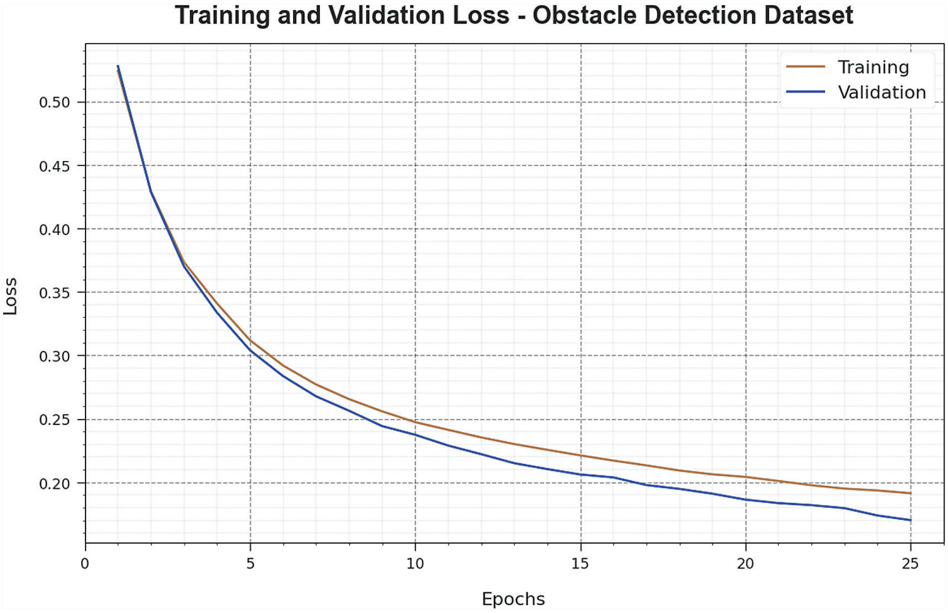

Figure 5: Loss curve of the SGDDL-ODC approach under obstacle detection dataset. Abbreviation: SGDDL-ODC, Stochastic Gradient Descent with Deep Learning-assisted Object Detection and Classification.

accuracy portrayed that the SGDDL-ODC approach learns productively on the obstacle detection database.

The loss analysis of the SGDDL-ODC method in the training and validation is shown on the obstacle detection database in Figure 5. The results indicate that the SGDDL-ODC method reaches adjacent values of training and validation loss. The SGDDL-ODC technique learns productively on the obstacle detection database.

In Table 2 and Figure 6, the scene recognition outcomes of the SGDDL-ODC approach are compared with the DeepNavi approach. The results indicate that the SGDDL-ODC technique gained increased $accu_y$ under all classes. For example, on the balcony class, the SGDDL-ODC technique achieves a higher $accu_y$ of 94.88% while the DeepNavi method obtains a lower $accu_y$ of 86.20%. Also, in the basement class, the SGDDL-ODC approach attains a higher $accu_y$ of 95.54% while the DeepNavi method obtains a lower $accu_y$ of 81.20%.

Table 2: $Accu_y$ analysis of the SGDDL-ODC approach with other methods under scene recognition dataset.

Scene recognition Class	DeepNavi	SGDDL-ODC
Balcony	86.20	94.88
Basement	81.20	95.54
Bridge	88.20	96.68
Bus station	83.60	94.91
Cafeteria	88.10	95.76
Crosswalk	85.50	93.41

Abbreviation: SGDDL-ODC, Stochastic Gradient Descent with Deep Learning-assisted Object Detection and Classification.

Additionally, on the bridge class, the SGDDL-ODC approach attains a higher $accu_y$ of 96.68% while the DeepNavi method obtains a lower $accu_y$ of 88.20%. In the meantime, in the bus station class, the SGDDL-ODC technique attains a

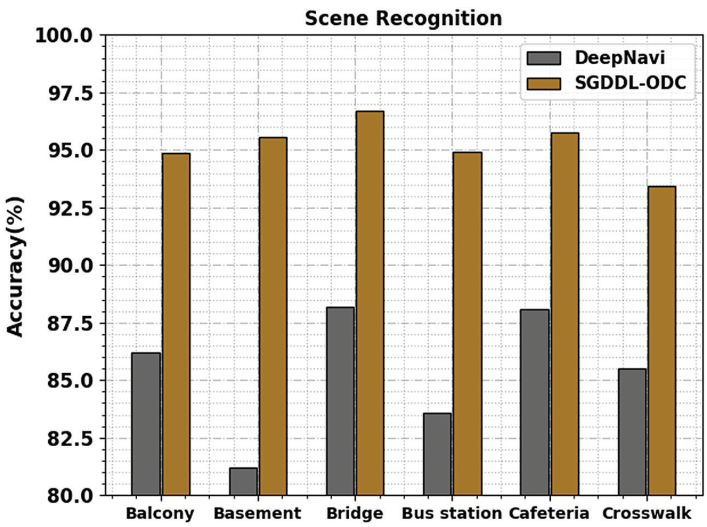

Figure 6: $Accu_y$ analysis of the SGDDL-ODC approach under scene recognition dataset. Abbreviation: SGDDL-ODC, Stochastic Gradient Descent with Deep Learning-assisted Object Detection and Classification.

higher $accu_y$ of 94.91% while the DeepNavi approach gains a lower $accu_y$ of 83.60%. Eventually, in the cafeteria class, the SGDDL-ODC technique attained a higher $accu_y$ of 95.76% while the DeepNavi model obtained a lower $accu_y$ of 88.10%. Finally, in the crosswalk class, the SGDDL-ODC technique accomplishes a higher $accu_y$ of 93.41% while the DeepNavi model obtains a lower $accu_y$ of 85.50%.

Figure 7 inspects the accuracy of the SGDDL-ODC method during the training and validation of the scene recognition database. The result notifies that the SGDDL-ODC technique has greater accuracy values over higher epochs. Also, the higher validation accuracy over training accuracy portrayed that the SGDDL-ODC method learns productively on the scene recognition database.

The loss analysis of the SGDDL-ODC technique in the training and validation is given on the scene recognition database in Figure 8. The results indicate that the SGDDL-ODC technique reaches closer values of training and validation loss. The SGDDL-ODC method learns productively on a scene recognition database.

CONCLUSION

This study has presented a new SGDDL-ODC method to detect and classify objects for visually challenged people. The main intention of the SGDDL-ODC technique concentrates

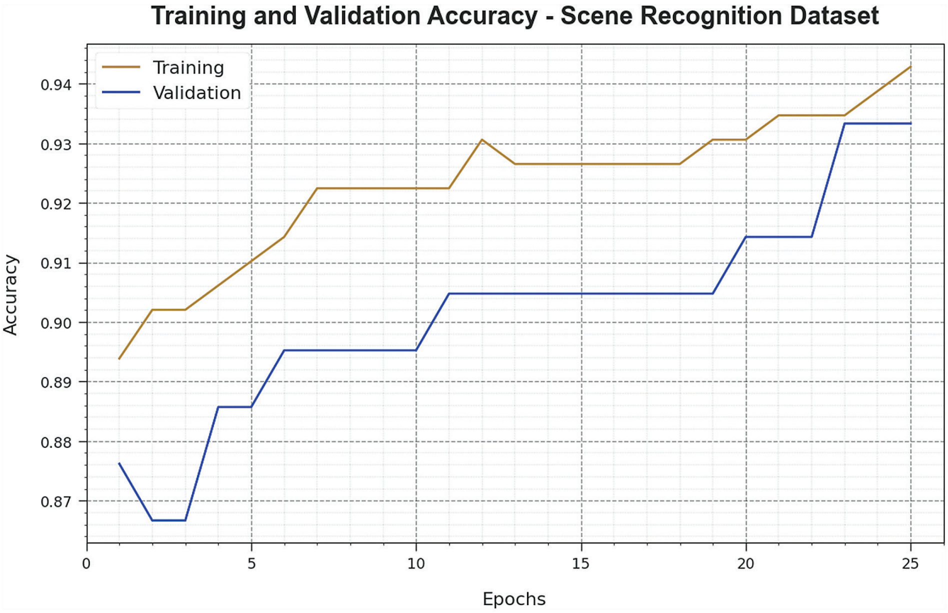

Figure 7: Accuracy curve of the SGDDL-ODC approach under scene recognition dataset. Abbreviation: SGDDL-ODC, Stochastic Gradient Descent with Deep Learning-assisted Object Detection and Classification.

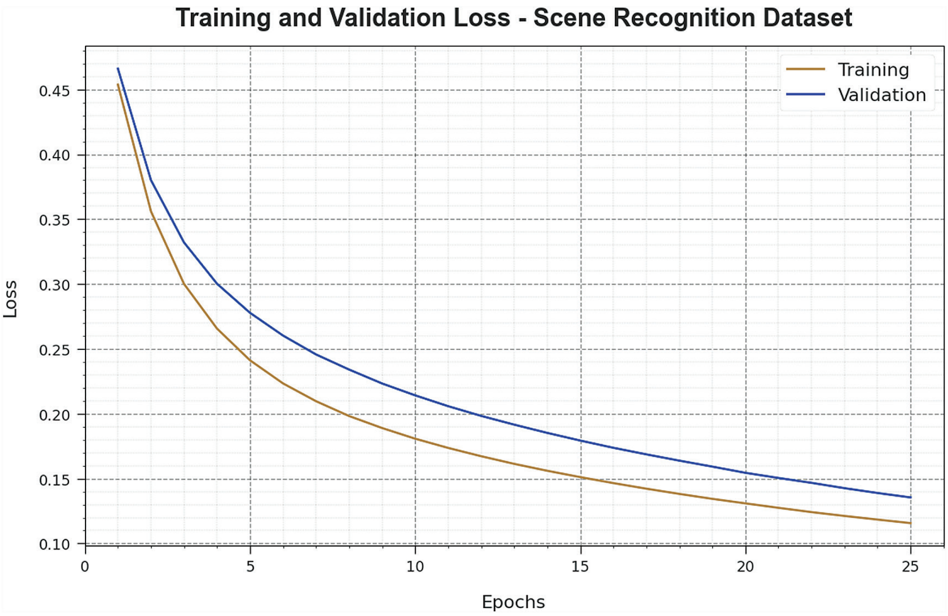

Figure 8: Loss curve of the SGDDL-ODC approach under scene recognition dataset. Abbreviation: SGDDL-ODC, Stochastic Gradient Descent with Deep Learning-assisted Object Detection and Classification.

on the accurate and automated detection of objects to help visually challenged people. To obtain this, the SGDDL-ODC technique focused on the development of the optimum hyperparameter tuning of the DL models effectively. To accomplish this, the SGDDL-ODC technique follows the YOLOv6 model for object detection purposes. The SGD model can be applied to adjust the hyperparameter values of the YOLOv6 method. At the final stage, the DNN model can be exploited for the classification of the recognized objects. Simulations were performed to validate the improved performance of the SGDDL-ODC technique. The simulation results illustrate the superior efficiency of the SGDDL-ODC technique exhibiting outcomes of 96.58 and 96.68% over other techniques under diverse datasets in terms of different measures. The limitations of the SGDDL-ODC technique lie in adapting to complex and dynamic environments, such as crowded or rapidly changing scenes, which could pose challenges for the technique, potentially leading to inaccuracies or missed detections. Also, the considerable computational resources required for real-time implementation may limit its practical deployment, especially in resource-constrained settings.

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CONFLICTS OF INTEREST

The authors declare no conflicts of interest in association with the present study.

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