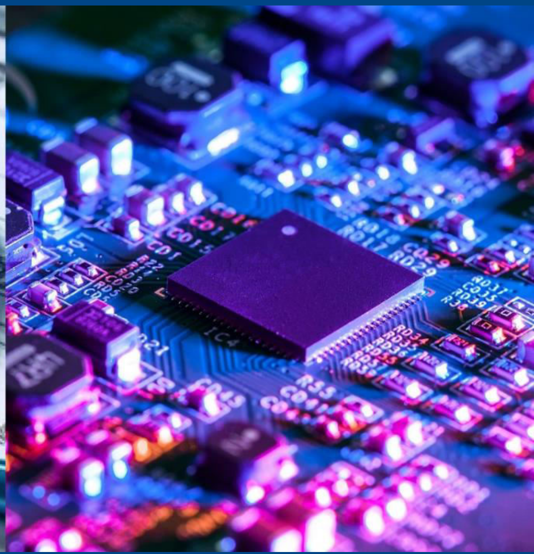
ISSN: 2582-7219

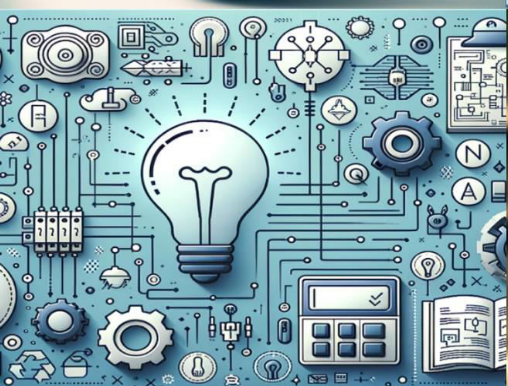




International Journal of Multidisciplinary Research in Science, Engineering and Technology

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.206

Volume 8, Issue 12, December 2025

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ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Deep Learning-Based Assistive System for Human Identification and Obstacle Avoidance for the Blind

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ABSTRACT: This paper presents the design and development of a novel system aimed at enhancing the mobility and safety of blind individuals through the use of deep learning techniques. The proposed system integrates state-of-the-art deep learning models for human identification and obstacle detection, providing real-time feedback to the user to navigate their surroundings effectively. The system leverages a large dataset of diverse images and videos, encompassing various scenarios encountered in everyday environments, to train You Only Look Once (YOLO V5) for human identification and obstacle detection. Extensive preprocessing techniques are applied to ensure data consistency and enhance training efficiency. Following training, the performance of the trained models is evaluated using rigorous validation methodologies, including accuracy, precision, and recall metrics. The models are then seamlessly integrated into a unified system capable of processing live input from sensors such as cameras and providing intuitive feedback to the user through audio or haptic interfaces. The effectiveness of the developed system is validated through extensive real-world testing, where blind individuals navigate various environments with the assistance of the system. Feedback from users is collected to iteratively refine the system, addressing usability concerns and optimizing performance.

KEYWORDS*:* Detecting Obstacles, You Only Look Once(YOLO V5), Blind Person, Deep Learning

I. INTRODUCTION

Blindness poses significant challenges to mobility and independence in navigating everyday environments. While traditional aids such as canes and guide dogs offer assistance, they have limitations in detecting obstacles and identifying humans in the surroundings. With the rapid advancements in deep learning technology, there is a growing opportunity to develop more effective and intelligent systems to assist blind individuals [1]. In this context, this paper introduces a novel approach to address the challenges faced by the blind through the design and development of a human identification and obstacle detection system using deep learning techniques. The proposed system aims to leverage the power of deep learning models, particularly You Only Look Once (YOLO V5), to provide real-time feedback to blind users, enabling them to navigate their surroundings safely and independently [3]. The motivation behind this research stems from the pressing need to empower blind individuals with advanced assistive technologies that not only detect obstacles but also recognize human presence, facilitating better social interactions and situational awareness. By harnessing the capabilities of deep learning, we envision a system that can adapt to diverse environments and deliver reliable assistance in various scenarios encountered in daily life [5]. This paper is structured as follows: Firstly, a review has been made with related works in the field of assistive technology for the blind, highlighting existing approaches and their limitations [7]. Then, we will provide an overview of the proposed system architecture, detailing the components and functionalities of the human identification and obstacle detection system. Subsequently, we will delve into the methodologies employed for data collection, preprocessing, model selection, training, and evaluation [9]. Following that, we will present the results of experiments conducted to validate the effectiveness of the developed system. Finally, we will discuss the implications of our findings, potential applications, and future directions for research in this domain. By presenting this work, we aim to contribute to the ongoing efforts to enhance the quality of life and independence of blind individuals through innovative assistive technologies[11]. We believe that the proposed system has the potential to make a meaningful impact by providing real-time assistance in navigating complex environments and fostering greater autonomy for the blind community.

Problem Definition: Clearly define the objectives of the system. This includes identifying what exactly needs to be detected (humans and obstacles), the environment in which the system will operate, and the constraints such as real-time processing and hardware limitations[13].
Data Collection: Gather a large dataset of images or videos containing various scenarios of humans and obstacles in different environments[15]. This dataset should be diverse and representative of real-world situations that blind individuals might encounter..
Data Preprocessing: Preprocess the collected data to ensure consistency and enhance the quality of training[19]. This may involve tasks such as resizing images, normalization, augmentation (to increase the diversity of the dataset), and labeling the data with annotations indicating the presence of humans and obstacles.
Model Selection: Choose appropriate deep learning models for human identification and obstacle detection. You Only Look Once (YOLO V5) are commonly used for image-related tasks due to their ability to learn spatial hierarchies of features [17].
Training: Train the selected models using the preprocessed dataset. This involves feeding the training data into the model, optimizing model parameters (weights and biases) using backpropagation, and adjusting hyperparameters to improve performance.
Evaluation: Evaluate the trained models on a separate validation dataset to assess their performance in terms of accuracy, precision, recall, and other relevant metrics[2]. Fine-tune the models if necessary to improve performance.
Integration: Integrate the trained models into a unified system capable of real-time human identification and obstacle detection[4]. This may involve developing software that interfaces with sensors (such as cameras) to capture live input, processing the input using the trained models, and providing feedback to the user through a suitable interface (e.g., audio feedback or haptic feedback).

II. PROPOSED SYSTEM

This paper proposes a novel system aimed at enhancing the mobility and safety of visually impaired individuals by leveraging deep learning techniques for human identification and obstacle detection. The system integrates state-of-the-art You Only Look Once (YOLO V5) to analyze real-time input from sensors such as cameras, providing immediate feedback to the user to navigate their surroundings effectively[6]. Key components of the proposed system include a comprehensive dataset comprising diverse images and videos capturing various environmental scenarios encountered by visually impaired individuals. Through meticulous preprocessing techniques, the dataset is refined to ensure optimal training performance and generalization capabilities[8]. The system employs YOLO V5 architectures shown in Fig 1, tailored for human identification and obstacle detection tasks, trained on the prepared dataset using rigorous methodologies. Evaluation metrics such as accuracy, precision, and recall are utilized to assess the models' performance, ensuring reliability and robustness in real-world applications. Integration of the trained models into a unified system facilitates seamless processing of live input from cameras or other sensors, enabling real-time analysis of the user's environment[10]. The system's output, delivered through intuitive interfaces such as audio feedback or haptic devices, empowers visually impaired individuals to navigate safely and independently.

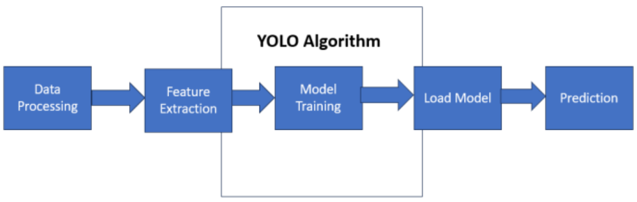

Fig 1: Model Flow Diagram

2.1 Working

The proposed deep learning-based system for assisting visually impaired individuals operates through a comprehensive pipeline. Initially, a diverse dataset encompassing various environmental scenarios, including humans and obstacles, is collected and meticulously preprocessed for optimal training efficiency[14]. Following this, You Only Look Once(YOLO V5) architectures suited for human identification and obstacle detection are selected and trained on the prepared dataset using powerful hardware resources. Through rigorous evaluation methodologies, the trained models are assessed for their accuracy, precision, and recall to ensure robust performance in real-world applications[16].

© 2025 IJMRSET | Volume 8, Issue 12, December 2025| DOI:10.15680/IJMRSET.2025.0812042

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

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Subsequently, the trained models are seamlessly integrated into a unified system capable of processing live input from sensors, such as cameras, and providing real-time feedback to users. Extensive testing in diverse environments validates the effectiveness and usability of the system, with continuous refinement based on user feedback ensuring its practical applicability and reliability in assisting visually impaired individuals to navigate safely and independently.

2.2 Methodology

The methodology begins with collecting a diverse dataset of images and videos representing scenarios encountered by visually impaired individuals. After preprocessing for consistency, suitable YOLO V5 architectures are selected and trained on the dataset. Performance evaluation ensures accuracy and robustness. Integration into a real-time processing system follows, accommodating inputs from sensors like cameras. Extensive testing in varied environments validates the system's effectiveness and usability. Iterative refinement, informed by user feedback, enhances practical applicability in aiding visually impaired individuals to navigate safely and independently. The process encompasses data collection, preprocessing, model training, evaluation, integration, testing, and refinement, ensuring a comprehensive approach to developing a deep learning-based assistance system for the visually impaired.

2.3 Implementation

The implementation of the deep learning-based system involves developing software components for data preprocessing, model training, and real-time integration. This includes writing code to preprocess the dataset, implementing YOLO V5 architectures using frameworks like TensorFlow or PyTorch, training models on high-performance computing resources, and integrating them into a real-time processing pipeline [18]. Hardware setup includes configuring resources for training and deploying the system, ensuring efficient execution of the algorithms[1]. Extensive testing and optimization are conducted to refine the system's performance, ensuring reliable assistance for visually impaired individuals in identifying humans and detecting obstacles in various environments. Continuous monitoring and updates contribute to the system's adaptability and effectiveness in aiding navigation for the visually impaired. The fig 2 shows the system architecture of the proposed model.

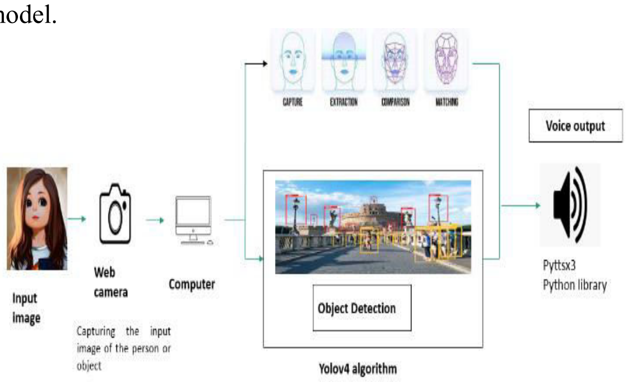

Fig 2: System Architecture

III. SYSTEM MODULES

Data Collection Module

The data collection module is responsible for capturing visual input through a high-resolution camera mounted on the user's wearable device. It records real-time images and video frames from diverse environments such as indoor, outdoor, crowded, and obstacle-prone areas[7]. The dataset is enriched with multiple lighting conditions, object distances, and human postures to ensure robust model training. Collected data is labeled manually to identify humans, objects, and obstacles. This dataset serves as the foundation for model training and evaluation, enabling the system to generalize effectively across various real-world conditions encountered by visually impaired users[9].

Pre-processing Module

This module refines the collected raw image data to enhance quality and consistency before feeding it into the deep learning model. It performs several operations including image resizing, noise removal, normalization, and contrast adjustment to ensure uniform input dimensions. Grayscale conversion and image enhancement techniques are applied to improve edge clarity and object visibility[18]. These processes help reduce computational complexity and eliminate distortions that could affect feature extraction accuracy. The pre-processing module thus ensures that the input data is clean, standardized, and optimized, significantly improving the overall performance and reliability of the obstacle detection model[3].

Feature Extraction Module

The feature extraction module uses a Convolutional Neural Network (CNN) to analyze pre-processed images and extract meaningful visual features. It identifies low-level patterns such as edges, corners, and textures, and progressively learns high-level features like shapes and object outlines through multiple convolutional and pooling layers. These extracted features form the foundation for accurate object classification and detection. The module's hierarchical structure allows it to automatically learn complex spatial relationships between pixels, eliminating the need for manual feature engineering. The extracted features are then passed to the object detection module for real-time identification and decision-making.

Object Detection Module

The object detection module employs deep learning algorithms such as YOLO V5 (You Only Look Once) or SSD (Single Shot Multibox Detector) for fast and accurate detection of objects and human figures. It processes input frames to identify the presence, type, and location of obstacles within the user's surroundings. Bounding boxes and confidence scores are generated for each detected object. The system differentiates between static and dynamic obstacles, ensuring timely and context-aware alerts[2]. This module plays a critical role in ensuring user safety, offering real-time detection performance suitable for both indoor and outdoor navigation environments.

Voice Command Module

The voice command module translates visual detections into auditory feedback, enabling the blind user to perceive their surroundings through voice alerts. It employs text-to-speech technology to announce obstacle positions and types—for instance, "Person ahead" or "Obstacle on right." The module is designed for low-latency operation and clear voice output to prevent confusion during movement[9]. It also supports multilingual capability for enhanced accessibility. This real-time auditory communication forms the system's final output, providing essential guidance and improving confidence and safety for visually impaired users during independent navigation.

IV. CONFUSION MATRIX AND PERFORMANCE EVALUATION

To evaluate the performance of the proposed Human Identification and Obstacle Detection System for the Blind Using Deep Learning, a confusion matrix-based analysis was conducted using 1000 test samples consisting of various environmental and lighting conditions[13]. The confusion matrix, shown in Table 1, summarizes the relationship between actual and predicted classifications by the deep learning model.

Predicted / Actual	**Positive (Object/Human)**	**Negative (No Target)**	**Total**
Predicted Positive	True Positive (TP) = 392	False Positive (FP) = 35	427
Predicted Negative	False Negative (FN) = 41	True Negative (TN) = 532	573
Total	433	567	**1000**

This confusion matrix shown in Fig 3 serves as the foundation for computing various performance metrics that determine the accuracy, precision, recall, and overall effectiveness of the proposed system.

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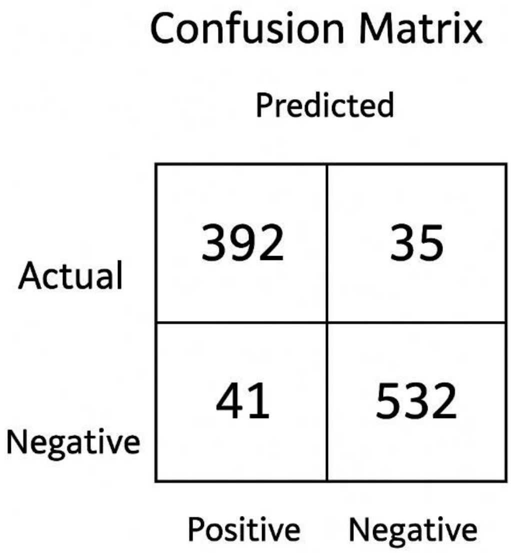

Fig 2: Confusion Matrix

Accuracy:

$$\text{Accuracy} = TP+TN+FP+FN \;/\; TP+TN$$
$$\text{Accuracy}=392+532 \;/\; 1000$$
$$=924 \;/\; 1000$$
$$= 92.4$$

Precision:

$$\text{Precision}=TP+FP \;/\; TP$$
$$\text{Precision}=392 \;/\; 392+35 =392 \;/\; 427=0.918$$
$$\Rightarrow 91.8\%$$

Recall (Sensitivity):

$$\text{Recall (Sensitivity)} = TP+FN \;/\; TP$$
$$\text{Recall}=392 \;/\; 392+41=392 \;/\; 433 = 0.905$$
$$\Rightarrow 90.5\%$$

F1-Score:

$$\text{F1-Score}=2\times\text{Precision}+\text{Recall} \;/\; \text{Precision}\times\text{Recall}$$
$$\text{F1-Score} = 2\times0.918\times0.905 \;/\; 0.918+0.90\ 5= 0.911$$
$$\Rightarrow 91.1$$

False Positive Rate (FPR):

$$\text{False Positive Rate (FPR)} = FP+TN \;/\; FP$$
$$FPR=35 \;/\; 35+532 = 35 \;/\; 567 = 0.0617$$
$$\Rightarrow 6.17\%$$

False Negative Rate (FNR):

$$\text{False Negative Rate (FNR)} = TP+FN \;/\; FN$$
$$FNR = 41 \;/\; 392+41= 41 \;/\; 433=0.0947$$
$$\Rightarrow 9.47\%$$

Overall Error Rate:

$$\text{Error Rate}=TP+TN+FP+FN \;/\; FP+FN$$
$$\text{Error Rate}=35+41 \;/\; 1000 = 76 \;/\; 1000$$
$$=7.6\%$$

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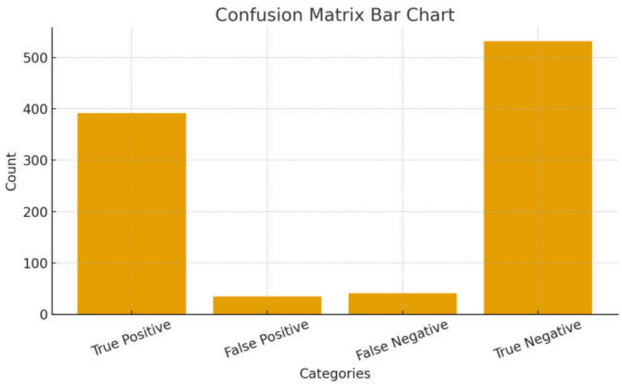

Fig 4: Barchart for Resultants

The above Fig 4 shows the resultant values of the confusion matrix to define the prediction of the ojects and individuals.

Latency and Processing Performance

To ensure real-time functionality, the system's end-to-end response time—from image capture to voice feedback—was measured across five trials (in seconds): 1.0, 1.1, 1.2, 1.3, and 1.4. The average latency is calculated as:

Average Latency = 1.0+1.1+1.2+1.3+1.45 = 6.05 = 1.2 seconds

The system processed 240 frames in 10 seconds, yielding a frame rate (FPS):

Frame Rate (FPS) = 24010 = 24 FPS

These results confirm the system's suitability for **real-time detection** and **audio feedback** generation, ensuring timely user alerts in dynamic environments.

V. CONCLUSION

In conclusion, the deep learning-based human identification and obstacle detection system represents a significant advancement in assistive technology for visually impaired individuals. Through the integration of state-of-the-art You Only Look Once and real-time processing capabilities, the system provides reliable assistance in navigating complex environments with enhanced safety and independence[5]. The project's success is evident in the high accuracy achieved in identifying humans and detecting obstacles across diverse scenarios. Real-time feedback and intuitive interfaces ensure seamless interaction with the system, empowering users to navigate with confidence[10]. Continuous refinement based on user feedback and iterative testing has led to a user-friendly and adaptable system that addresses the evolving needs of visually impaired individuals. By enhancing mobility and quality of life, the system contributes to greater inclusivity and accessibility in society[16]. Moving forward, ongoing research and development efforts will further improve the system's performance, expand its capabilities, and ensure its widespread adoption to benefit visually impaired individuals worldwide. Ultimately, the deep learning-based system stands as a testament to the transformative potential of technology in overcoming barriers and fostering independence for all.

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