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INVESTIGATION OF COMPUTER VISION TECHNIQUES FOR INDOOR NAVIGATION SYSTEMS

The subject of this article is the development and implementation of computer vision methods that can be integrated into an indoor navigation system designed for individuals with visual impairments. **The goal** of the study is to enhance such a system with advanced object recognition capabilities in enclosed environments by combining modern technologies, including artificial intelligence, spatial analysis, voice control, and Bluetooth-based localization. To achieve this, a number of **tasks** were carried out. These included an analysis of the problem domain and justification of the study's relevance, a comparison of existing solutions, and the development of a generalized model of the navigation system with a voice interface, enabling real-time search for locations and items. A specialized dataset was prepared, containing images of key obstacle classes typically encountered in indoor environments – such as shopping carts, barrier tape, forklifts, and people. A new two-stage object recognition method was proposed to detect these classes in complex scenes. Additionally, a comparative analysis of deep learning architectures for object detection was conducted, followed by experimental studies to assess training quality and system robustness. The research employed various image preprocessing **methods** – bilateral filtering, Gaussian blurring, enhancement of specific color channels, motion blur removal, and noise reduction using averaging filters – as well as neural network-based methods for data analysis and statistical evaluation approaches. The **results** demonstrate that the proposed method significantly improves object detection performance on real-world images, achieving an average intersection-over-union (IoU) of 68% and a confidence level of 69%, which is 79% and 89% higher, respectively, compared to baseline recognition results on noisy inputs. However, the findings also revealed the necessity of integrating additional sensors, such as LiDAR, to reliably detect low-contrast or reflective obstacles like glass storefronts, which are difficult to identify using computer vision alone. **Conclusions.** The study confirms that the proposed two-stage preprocessing, and recognition pipeline significantly enhances navigation system performance for users with visual impairments, while also highlighting the importance of combining vision-based methods with complementary sensing technologies to ensure safe and reliable operation in complex indoor environments.

Keywords: system; localization; navigation; blindness; recognition; computer vision; classification.

Introduction

Vision impairments lead to a lower quality of life, especially in large cities with complex navigation environments. They also reduce independence, autonomy, and overall safety. Therefore, the task of creating robotic assistants based on artificial intelligence or developing technological solutions capable of ensuring comfort, safety, mobility, and independence remains highly relevant [1–3].

In Ukraine, there is a growing number of people with visual impairments. According to the National Health Service of Ukraine (NHSU), in 2021, 17,478 people were diagnosed with blindness or vision impairment. In 2022, this number increased to 19,551 people. Moreover, in the first seven months of 2023, the number of registered cases has already reached 19,336 patients, which is close to the total number for the previous year.

These data and the growing number of people with visual impairments highlight the social need for and importance of developing indoor and outdoor navigation systems. Such systems are important for the accessibility

and independence of people with visual impairments. The implementation of these navigation systems is in line with the objectives of the European Disability Strategy, ensuring social integration and equal access to infrastructure, public services, and employment opportunities for people with disabilities.

Analysis of last achievements and publications

Computer vision (CV) is a field of artificial intelligence that teaches computers to interpret and understand the visual world. Using digital images from cameras and videos, as well as deep learning models, computers can accurately identify and classify objects and then respond to what they "see". At the heart of CV is image processing, which involves improving image data (removing noise, sharpening or brightening the image) and preparing it for further analysis.

Computer vision is actively being implemented in various industries, improving accuracy and speed of work, as well as automating complex processes. These examples confirm that computer vision (CV) already plays a key role in the future of technology (Fig. 1) [4–8].

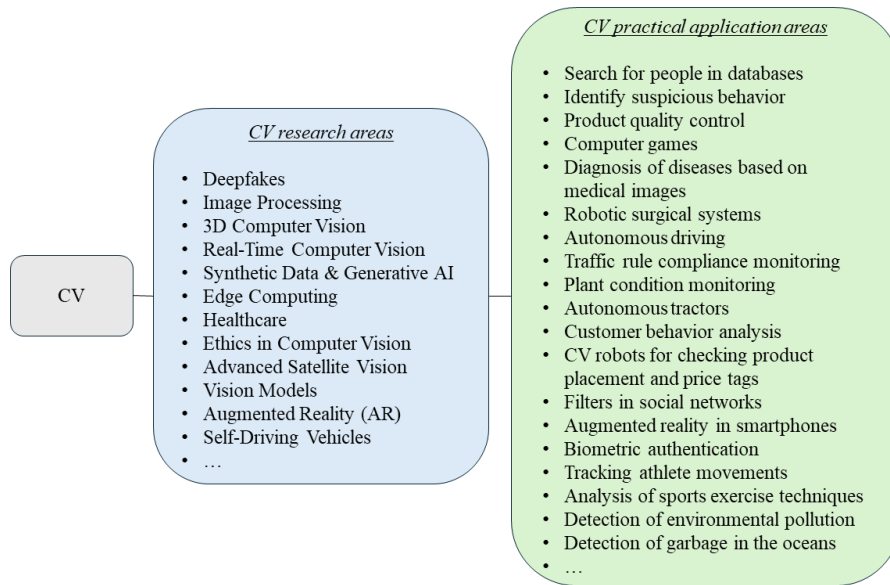


Fig. 1. Some of computer vision research and practical application areas overview

Detecting obstacles for a blind person's shopping cart in a supermarket can be considered a special case of real-time computer vision (real-time CV) and autonomous navigation. The system can use cameras, LiDAR, depth sensors, and modern CV models to analyze the path and warn the user about obstacles using voice commands or tactile feedback.

Modern deep learning architectures for computer vision tasks can be divided into several categories:

- convolutional neural networks (CNNs);
- transformers;

- hybrid models;
- generative networks.

Below is a comparison table of modern deep learning architectures used for various computer vision tasks (Table 1). The table presents the key characteristics of the models, including the year of development, the number of parameters, accuracy on known datasets (ImageNet, COCO), image output speed, and real-world application areas. The architectures are grouped by type: convolutional neural networks (CNNs), transformers, hybrid models, and generative networks.

Table 1. A comparative table highlighting key characteristics of various deep learning architecture classes used in computer vision

Model Name	Year	Parameters	Top-1 Accuracy (ImageNet)	Top-1 Accuracy (COCO)	Inference Speed (ms/image)	Real-world Applications	Datasets Used
1	2	3	4	5	6	7	8
Architecture Type: Convolutional Neural Networks							
ResNet-50	2015	25.6M	79%	–	4.6	Image classification, Feature extraction	ImageNet [9]
DenseNet-121	2016	8.0M	74.9%	–	6.9	Medical imaging, Anomaly detection	ImageNet [10]
EfficientNet-B0	2019	5.3M	77.1%	–	3.2	Mobile vision applications	ImageNet [11]
Faster R-CNN	2015	41.0M	–	42.0%	100+	Object detection, Autonomous driving, Medical imaging	COCO, Pascal VOC [12]
Architecture Type: Transformers							
Vision Transformer (ViT-B/16)	2020	86.4M	77.9%	–	7.9	Large-scale image classification	ImageNet [13]
Swin Transformer (Swin-B)	2021	88.0M	83.5%	53.5%	8.7	Object detection, Segmentation	ImageNet [14]
DETR	2020	41.5M	–	44.0%	50-60	Object detection, Autonomous systems, Retail AI	COCO, ADE20K [15]

Continuation of the table 1

1	2	3	4	5	6	7	8
Architecture Type: Hybrid Models							
ConvNeXt-B	2022	88.6M	83.8%	–	8.0	General-purpose vision tasks	ImageNet [16]
YOLOv8	2023	~25.0M	–	51.5%	5–10	Object detection, Surveillance, Robotics	COCO, OpenImages [17]
Architecture Type: Generative Networks							
BigGAN	2018	112.0M	–	–	–	Image synthesis, DeepFakes	ImageNet [18]

Analysis of the table showed that for the task of recognizing visual obstacles in the path of a shopping cart between aisles, it is important to focus on the following aspects:

- Speed of logical inference. YOLOv8 demonstrates the highest image processing speed (5–10 ms per image). This is critical for a task where obstacles must be detected in real time so that the cart can quickly respond to changes in the environment.

- Training on COCO and OpenImages. The YOLOv8 model was trained on COCO and OpenImages, which include many classes of objects found in real life (e.g., bottles, boxes, shopping carts). This allows the model to adapt to typical obstacles in a supermarket;

- Versatility. YOLOv8 supports detection, classification, and segmentation, allowing you to extend the functionality of the system. For example, you can use YOLOv8 not only for obstacle avoidance but also for environment analysis (product identification or navigation).

- Compact model (parameters). YOLOv8 has a relatively small number of parameters (~25 million) compared to other detectors (e.g., Faster R-CNN – 41 million). This makes YOLOv8 more suitable for use in devices with limited computing resources, such as carts with integrated cameras.

- Real-world use cases. YOLOv8 is already being used in video surveillance and robotics, where real-time object detection is also required. These examples confirm that YOLOv8 is well suited for dynamic environments such as supermarket traffic.

With its high social relevance, the project focuses on achieving scientific and engineering goals.

The aim of this research is to develop and implement artificial vision methods focused on indoor obstacle recognition in a proposed indoor navigation system for visually impaired people. The system integrates modern technologies such as artificial intelligence, voice control, spatial analysis, and Bluetooth-based navigation.

The system aims to promote social integration and increase the independence of visually impaired people

when navigating complex indoor environments such as shopping malls, warehouses, or public facilities.

The implementation of the project includes the following tasks:

- analysis of the problem area and justification of the relevance of the research topic;

- development of a model of an indoor navigation system with a voice interface for real-time search of places and objects by users with visual impairments;

- preparation of a working dataset containing images of specific classes – shopping carts, barrier tape, people, forklifts;

- creation of an improved method for object detection in complex scenes;

- conducting experimental studies to evaluate the quality of training and identify limitations and shortcomings in the use of visual detection tools.

Materials and methods

Based on the analysis of the subject area, the key components of the proposed system are as follows:

- voice message interpretation technology;
- interactive maps of premises with spatial localization of key objects;

- a system for positioning moving objects within a room;

- a subsystem for determining the route from a moving object to a destination point, provided in the form of a voice query.

A functional model of the system for planning a route to a specific place or product is shown in Figure 2. The diagram is used to determine the requirements for the system and to clarify the functions necessary for further development of the system.

To start working with the proposed route planning system for a specific location or product, it is necessary to obtain input data. The input data includes the user's local coordinates and voice command, the analysis of which determines the desired location or product for which a route needs to be built within the premises (indoor localization).

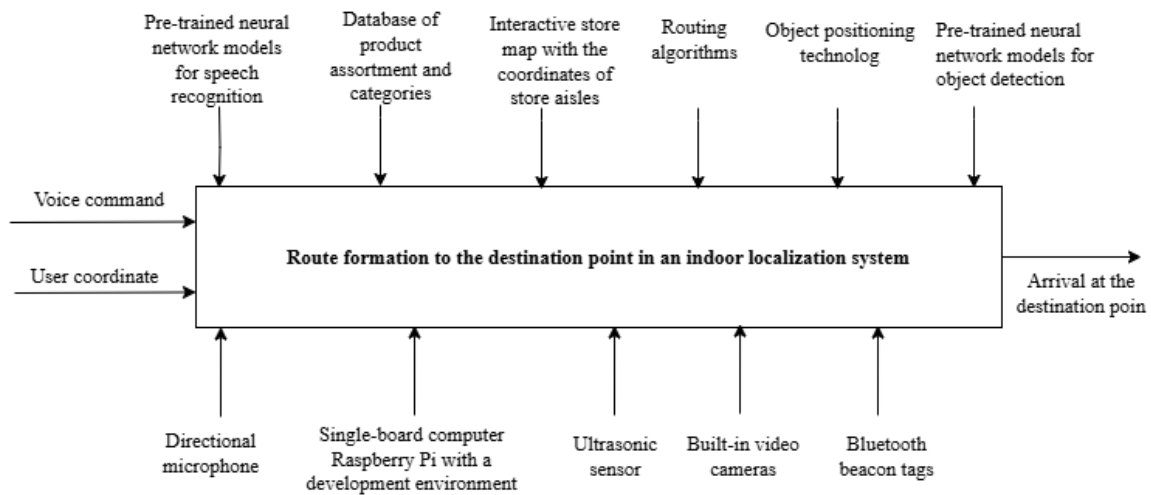


Fig.2. Generalized Functional Model of the System for Route Planning to a Specific Location or Product

As a result of decomposing the generalized functional model of the route planning system for a specific location or product, five structural blocks were identified: interpretation of a voice request into a command, determination of the destination coordinates, route construction, analysis of obstacles in the user's path, and reactive route updating (Figure 3).

To interpret a voice request into a command, the system uses the mathematical apparatus of artificial neural networks (ANN) and methods of preliminary processing of voice information, including normalization, reverberation reduction, compression, spectrogram equalization, and frequency filtering (using time and frequency masks).

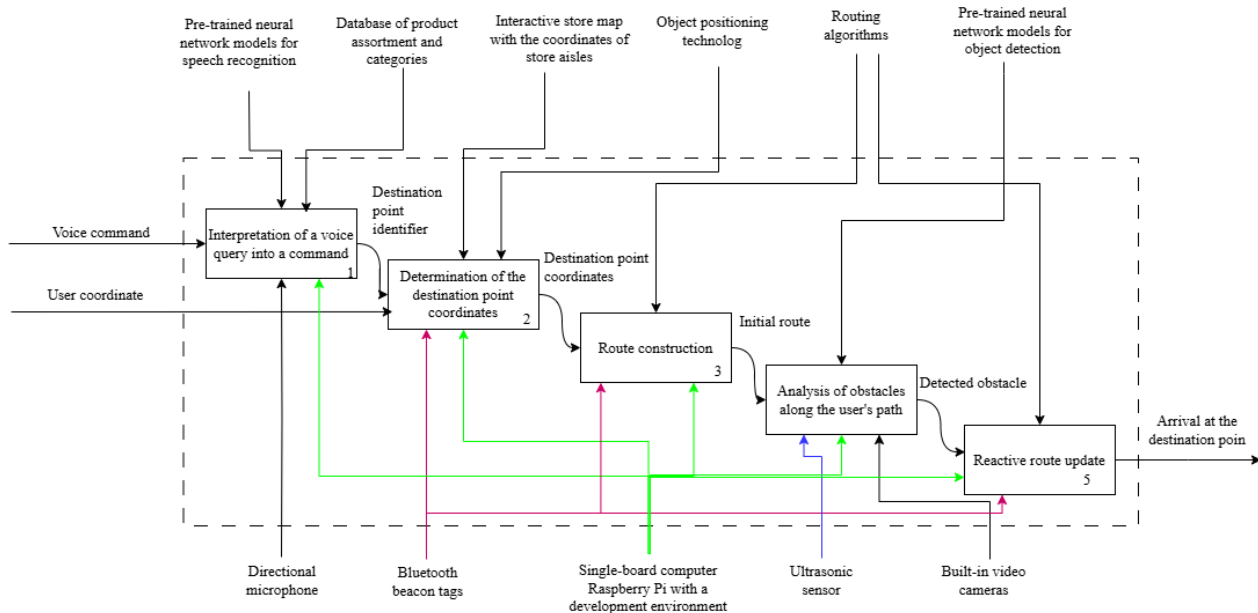


Fig.3. Decomposition of the Process into Interconnected and Interdependent Functional Blocks

The use of directional microphones allows the system to focus on sounds from a specific direction, ignoring noise from other sources. This approach significantly improves the signal-to-noise ratio (SNR), which is critical for accurate speech recognition.

To determine the location of the requested item, the system analyzes the product database, where all entries

are considered a training dictionary for the neural network during recognition.

The coordinates of the store aisles are stored on an interactive map of the premises, which links information about specific aisles (e.g., product assortment) to their physical location. This data is synchronized with positioning technology, allowing the system to accurately locate objects in space.

Object positioning in the system is implemented using Bluetooth Low Energy (BLE) beacons, which transmit signals with unique identifiers at fixed intervals (Figure 4). Compared to other positioning technologies (UWB, WiFi, RFID, optical systems, etc.), BLE technology offers several key advantages:

- high accuracy (up to 1-2 meters depending on the number of beacons and environmental conditions);
- energy efficiency;
- ease of deployment;
- scalability.

These characteristics make BLE a suitable choice for large, complex indoor environments such as shopping malls or warehouses.

Obstacles in the user's path are detected by analyzing the surrounding space. This information is processed by a Raspberry Pi single-board computer, which analyzes the input data and detects obstacles in the route. The system provides real-time obstacle detection, which is important for user safety and navigation accuracy.

Routing algorithms build the optimal and safest path to the requested product, taking into account the detected obstacles.

The system uses the user's current coordinates, and the coordinates of the destination point as input data.

The resulting route is presented to the user in the form of a series of voice instructions for smooth control.

The first stage of implementing the proposed system is to develop a model of a local navigation system with a voice interface, which serves as the initial step necessary for implementing the proposed system. This stage includes the following tasks:

- creation of a digital map of selected premises with the location of key objects;
- selection of positioning technology (Wi-Fi, Bluetooth beacons, UWB, ultrasound, etc.);
- development of a wireless personal area network (WPAN) model based on Bluetooth Low Energy (BLE) technology;
- integration of the BLE network into the RTLS system infrastructure (with the ability to add new objects and assign unique identifiers) to create an effective positioning and tracking mechanism in real time;
- integration of an algorithm for determining the current location of the user using an interactive map of the premises to display the current position of the user.

The second stage involves the development of a routing subsystem based on interactive floor plans for indoor navigation, which is another key step in the implementation of the proposed system.

This stage includes the following tasks:

- review of route planning algorithms, including triangulation algorithms, Dijkstra's algorithm, and SLAM;
- implementation of a method for detecting obstacles/moving objects;
- implementation of a context-dependent routing algorithm in the RTLS system, taking into account detected obstacles;
- development of methods for reactive route updating.

The most research-intensive stage necessary for the implementation of the proposed system is the study and development of methods for interpreting voice queries in an indoor navigation system. This stage is the most science-intensive, since the accuracy of voice query interpretation directly affects the accuracy of the generated route. This stage includes the following tasks:

- systematization of knowledge about hardware for voice capture in noisy environments;
- research of noise suppression methods and reduction of reverberation effects to minimize the impact of reflected sound on voice command recognition;
- evaluating the impact of using directional microphones or microphone arrays to improve voice command recognition accuracy by isolating the speaker's voice;
- developing methods for analyzing voice commands with adaptability to lexical ambiguity.

Further research in this work focuses on analyzing computer vision methods, which are the basis of the user interference analysis module. The YOLO8nano neural network model was trained on two prepared datasets. The key characteristics of the first dataset are as follows:

- the total volume is 300 images, divided into training (80%, 240 images) and test (20%, 60 images) subsets;
- includes four classes – faces (highlighted on a portion of images of other classes) and carts, forklifts, and barrier tape (100 images for each class). Image size varies from 141x149 to 2010x2010 pixels. The images were normalized and reduced to 640x640 for accurate neural network training.

The images were collected from random sources, so the quality varies:

- lighting – from bright to dim, both daylight and artificial;
- noise – JPEG compression artifacts, blur, some images have a "grainy" texture;
- viewing angle – images show objects from different angles and perspectives. However, preference was given to images where the viewing point is no lower

than one meter above the ground and no higher than human eye level.

The second dataset was a test dataset, and the model was trained on it separately, as training on this dataset could distort the weights of other classes. The key characteristics of the dataset are the same as for the first one, with the following exceptions:

- total volume is 100 images;
- it includes two classes: people (not labeled separately; pre-trained weights were left) and shop windows/glass walls (100 images (80 for the training set and 20 for the test set). The image size varies from 339x295 to 715x474.

Research results

This study focuses on the ability of a pre-trained neural network to accurately recognize four main classes of obstacles. The fifth class (glass walls/showcases) is a test class and is placed in a separate network, as it is predicted that the selected neural network is not capable of learning to recognize poorly visible objects, which

could ultimately reduce the detection accuracy of the other classes.

Since images are often accompanied by noise in real conditions, a two-stage detection algorithm is proposed, the essence of which is as follows:

- the input image is fed to the input of the neural network;
- after detecting an object in the image, if the confidence that this object belongs to a certain class is less than 85%, then preprocessing methods are applied to this image, depending on which class the neural network assigned the object to for the first time. After that, the image is fed back into the neural network;
- the neural network moves on to the next image or completes its work.

Figure 4 shows a simplified algorithm for analyzing obstacles in the path of the module user.

Table 2 shows the dependence of the IoU and Confidence metrics on the use of preprocessing methods on images with significant noise (from 21 to 55%). For simplicity, Table 3 shows only one experiment for each class.

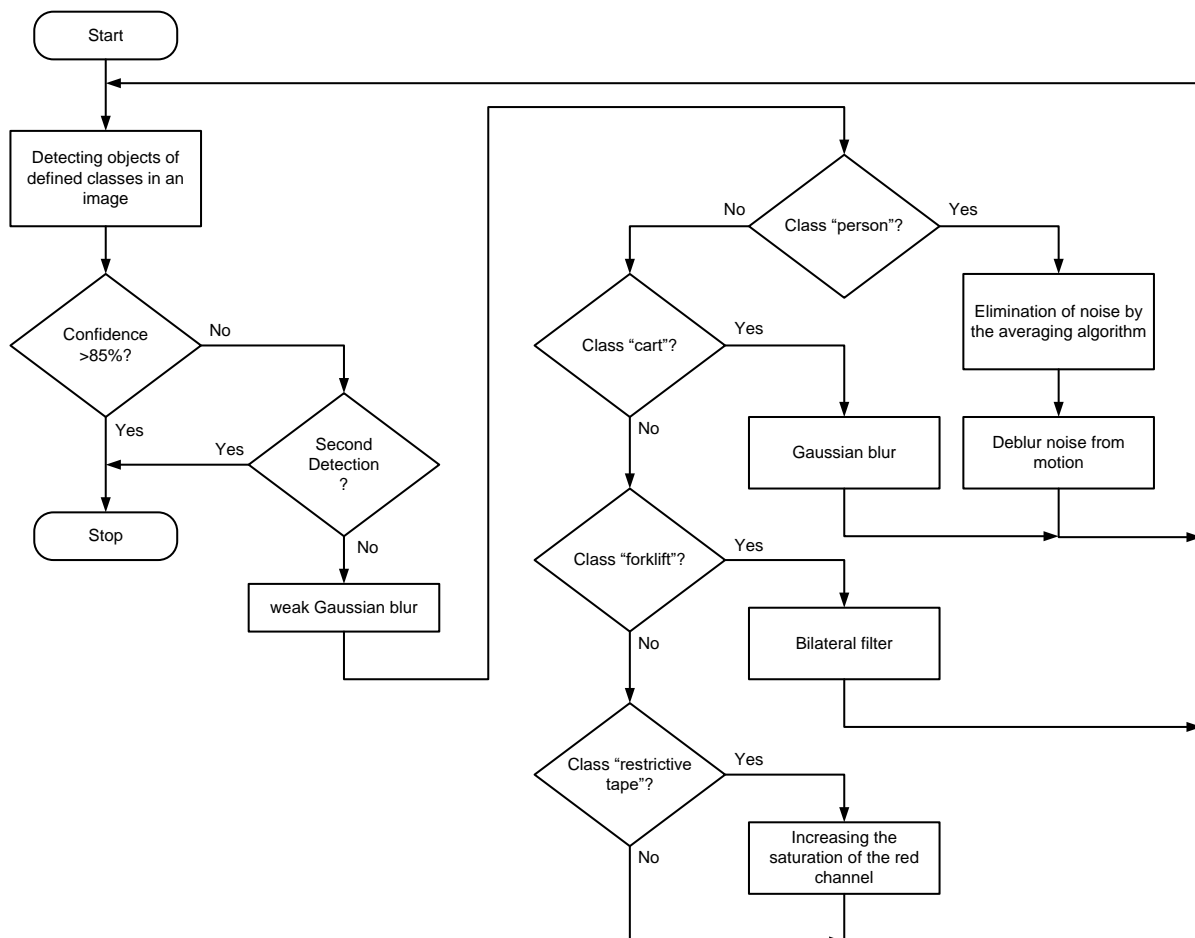


















Fig. 4. Simplified algorithm of the analysis of obstacles along the user's path module

Table 2. Results of experimental studies of the impact of using preprocessing methods on IoU and Confidence indicators for noisy input images

Cart recognition demonstration	Forklift recognition demonstration	People recognition demonstration	Restrictive tape recognition demonstration
Input noisy image			
			
Reference marked-up image			
			
Detected object in an image without preprocess-sing			
			
Average IoU and confidence for an image without preprocessing, %			
IoU = 65 conf. = 32	IoU = 57 conf. = 46	IoU = 36 conf. = 55	IoU = 25 conf. = 51
Detected object in the image after preprocessing			
			
Average IoU and confidence for pre-processed images, %			
IoU = 69 conf.= 81,5	IoU = 67 conf. = 72	IoU = 70 conf. = 61	IoU = 65 conf. = 63
Average increase in IoU and confidence when using preprocessing, %			
IoU = 15 conf. = 154	IoU = 47 conf. = 56	IoU = 94 conf. = 110	IoU = 160 conf. = 24

Analysis of the results presented in Table 3 shows that the use of image preprocessing methods improves the ability of the neural network (NN) to recognize objects.

On average, the IoU (intersection over union) metric can be increased by 79% and the Confidence metric by 86%. For better visualization, a summary graph of the averaged

IoU and Confidence metrics is provided for images without additional noise, noisy images, and images that have undergone preprocessing.

Table 3 shows the results of determining the training quality of NN YOLO8nano on a selected training dataset using averaged IoU (intersection over union) and confidence metrics using high-quality input images (noise level up to 20%).

The graph in Figure 5 clearly shows a trend toward improvement in the average IoU and Confidence metrics for images with noise when using preprocessing methods. In some places, when using preprocessing methods, the selected metrics exceed the IoU and Confidence for images without additional noise.

Table 3. Results of experimental studies of IoU and Confidence metrics for high-quality input images

	Cart	Forklift	People	Restrictive tape
Average class confidence, %	91	64	59	65
Average class IoU, %	80	58	62	71

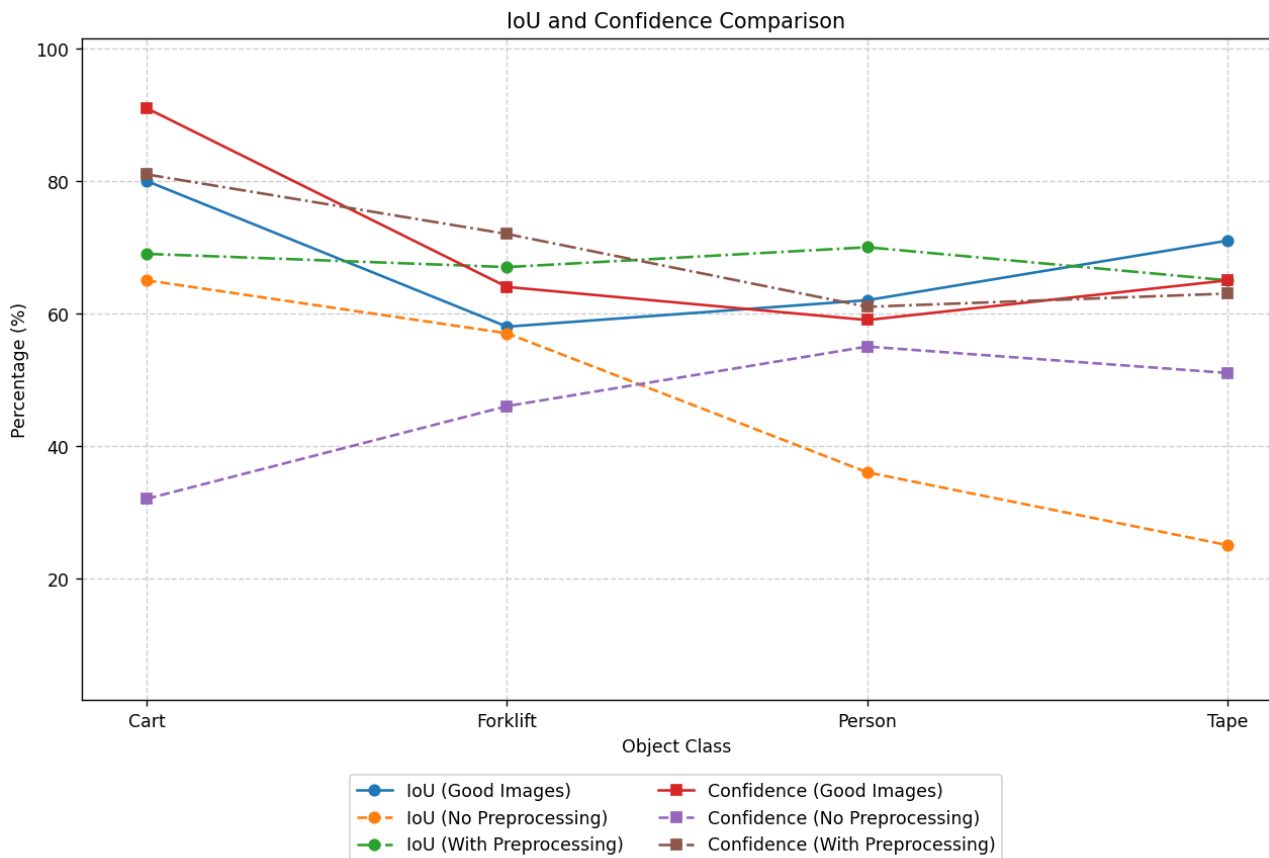


Fig. 5. Summary graph of averaged metrics

The last experiment analyzed the capabilities of computer vision methods for detecting poorly visible obstacles, such as glass windows/walls. Table 4 shows a selection of four experiments that reflect general trends in the object recognition results of a neural network trained on the second dataset. Table 4 shows that more

than half of the images of shop windows/glass walls are free of these obstacles. Thus, the use of photo and video sensors is insufficient to detect this class of obstacles. Therefore, it is advisable to equip the system with ultrasonic sensors or lidars to confirm the creation of such an object based on a significant distance to it.

Table 4. Evaluation of the ability of the selected neural network to detect faint objects after training on the selected dataset

input images	reference marked-up image	image with detected object
shopfront1.JPG (confidence=0.85)		
		
shopfront2.JPG (confidence=0.32)		
		
shopfront3.JPG (confidence=0.84)		
		
shopfront4.JPG (confidence=0.88)		
		

Conclusions

The relevance of the research is due to the growing number of people with visual impairments and the need to develop technologies that ensure their independence and safety in urban environments.

The practical significance lies in the creation of a technology that can be used in shopping centers, warehouse complexes, and public buildings to ensure the convenience and safety of people with visual impairments.

The scientific novelty lies in the development of an integrated system that combines computer vision for obstacle detection and their implementation in an adaptive routing subsystem, a voice interface for user interaction, and BLE navigation for indoor positioning.

The research aims to improve object recognition methods in commercial premises.

The results showed that the proposed two-stage recognition method based on YOLOv8 increases the confidence in detecting objects in the user's path (people, carts, forklifts, barrier tapes) by 89%, reaching an average confidence of 69%, while IoU increased by 79%, reaching an average IoU = 68%. A two-stage preprocessing algorithm is proposed, according to which the sequence of preprocessing methods for input images depends on a predefined class. It was also found that for some classes of obstacles (e.g., mirrors or glass showcases), the system requires additional tools to process additional data obtained from sensors that compensate for the limitations of photo and video cameras.

Prospects for further research. Future research aims to improve the system by adding specialized sensors for detecting hard-to-recognize objects and developing context-dependent routing methods in the proposed system.

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ДОСЛІДЖЕННЯ МЕТОДІВ ШТУЧНОГО ЗОРУ В СИСТЕМАХ ВНУТРІШНЬОЇ НАВІГАЦІЇ

Предметом статті є методи комп'ютерного зору, які можуть бути імплементовані у систему навігації в приміщенні для людей з вадами зору. **Метою цього дослідження** є розробка та впровадження методів штучного зору, орієнтованих на розпізнавання перешкод у закритому просторі, у пропоновану систему внутрішньої навігації для людей з вадами зору, яка інтегрує сучасні технології штучного інтелекту, голосового керування, просторового аналізу та Bluetooth-навігації. Для досягнення мети були вирішені такі **завдання**: виконано аналіз проблемної області, включаючи обґрунтування актуальності теми, порівняння існуючих рішень; запропоновано узагальнену модель системи з описом передбачених модулів; запропоновано новий метод розпізнавання основних класів перешкод, які можуть зустрітися в торгових залах (люди, візки, навантажувачі, обмежувальна стрічка) за допомогою вдосконаленого методу двоетапного розпізнавання об'єктів; проведено порівняльний аналіз архітектур глибокого навчання для задач розпізнавання об'єктів; виконано експериментальні дослідження для оцінки якості навчання. Використані **методи**: попередньої обробки зображення (білатеральна фільтрація, гаусівське розміття, підвищення насиченості певного каналу зображення, видалення розміття рухом, видалення шумів алгоритмом усереднення), неймережеві методи аналізу вхідних даних, методи статистичних досліджень. **Результат**: запропонований метод показав хороші результати на реальних тестових зображеннях. (досягнуто: IoU = 68% і достовірність = 69% в середньому, що в середньому на 79% і 89% більше, ніж вихідні зображення з шумом). Була виявлена необхідність розширення системи додатковими інструментами (наприклад, лідачами) для виявлення важко помітних перешкод типу дзеркальних вітрин. **Висновки**. Спираючись на проведений аналіз, запропонований двохетапний метод препроцесингу значно покращує якість розпізнавання. Пропонованій системі потрібні додаткові датчики, оскільки не всі об'єкти можуть бути розпізнані за допомогою методів комп'ютерного зору.

Ключові слова: система; локалізація; навігація; сліпота; розпізнавання; комп'ютерний зір; класифікація.

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