UDC 004.896:004.93’1:623.4 **doi: 10.26906/SUNZ.2025.3.117-121**

Denys Levchenko, Andrii Podorozhnyak, Nataliia Liubchenko

National Technical University «Kharkiv Polytechnic Institute», Kharkiv, Ukraine

TOOLS AND METHODS FOR EXPLOSIVE OBJECTS DETECTION USING ARTIFICIAL INTELLIGENCE AND COMPUTER VISION

Abstract. Relevance. The problem of detecting explosive ordnance remains one of the most acute in the modern world and in Ukraine, in particular due to the growing number of armed conflicts and contamination of territories with landmines and unexploded ordnance. Traditional methods of demining are time-consuming, dangerous, time-consuming and not always effective, necessitating the introduction of innovative technologies based on artificial intelligence and computer vision. **Object of research.** The object of research is intelligent tools and methods for detecting explosive objects, in particular the proposed prototype combining deep learning (YOLOv8) and robotic platforms for real time. **Purpose of the article.** The article is aimed at analyzing existing solutions, developing and experimentally testing an efficient, portable system for automated mine detection using lightweight deep learning models capable of operating on mobile devices in a variety of environmental conditions. **Research results.** Two specialized datasets covering different types of mines (POM-2, POM-3, PMA-2 "starfish") and various environmental conditions, soil types, weather factors and the presence of obstacles were used, modernized and annotated in the work. To speed up the training of the AI models, distributed and parallel computing are applied. The YOLOv8-nano and YOLOv8-small models demonstrated high precision (up to 98.8%) and recall for major landmine classes, which was confirmed by the analysis of confusion matrices and key metrics. The focus is on the development and research of a prototype system for automated landmine detection based on deep learning and computer vision, integrated with robotic platforms and unmanned aerial vehicles. The system provides real-time operation (2-2.6 frames per second) on mobile devices, has a simple architecture and the ability to integrate with robotic and unmanned platforms. **Conclusions.** The proposed system is promising for humanitarian demining due to its high accuracy, mobility and ease of deployment. At the same time, the results of the experiments indicate the need for further improvement of models to increase resistance to changes in environmental conditions and reduce the number of false positives. The implementation of such solutions will contribute to increasing the efficiency and safety of demining in post-conflict regions.

Keywords: unmanned ground operations, landmine detection, artificial intelligence, visual data processing, computer vision, distributed and parallel computing.

Introduction

Landmines and explosive ordnance continue to pose a significant humanitarian challenge, driven by the growing number of global conflicts. Vast land and urban areas remain contaminated with antipersonnel (AP) and antitank (AT) mines, as well as unexploded ordnances (UXOs), requiring decades for clearance using current technologies. Effective solutions demand improvements in detection, clearance, and victim assistance.

Traditional detection methods rely on metal detectors and ground-penetrating radar, often integrated into dual-mode handheld systems [1]. Recent advancements include UAV- or robot-mounted sensors such as microwave radar, infrared cameras, and magnetometers [2]. Surficial ordnance – either abandoned or cluster-deployed – also presents a growing risk, necessitating specialized detection tools.

Electronic sensors and AI-based image processing now enable autonomous systems capable of identifying and mapping surface threats. High-resolution cameras, paired with real-time AI analysis, offer reliable detection across varied environments. This study introduces a prototype system using a sensor-equipped, remotely operated robotic platform for detecting visible surface UXOs, notably the PFM-1 and PMA-2 plastic landmines, which remain common and deadly in post-conflict zones.

Recent efforts in object detection, particularly through deep learning, have enhanced identification accuracy across multiple fields – including autonomous navigation, surveillance, and now humanitarian demining. Both CNN- and transformer-based models can analyze high-resolution imagery, though not all support real-time inference. The YOLO architecture was selected for its speed, efficiency, and portability.

The proposed system integrates real-time detection with robotic mobility, adaptable to additional platforms such as UAVs. This research presents a lightweight and high-recall solution tailored to operational constraints, addressing a critical gap in landmine detection through a practical, deployable, and scalable approach [3].

Analysis of proposed system implementation. The "Demining Robots" project deploys autonomous robots for landmine detection and removal. The UGO (Unmanned Ground Operations) robot is key in detecting surface landmines, using LiDAR, holographic radar, accelerometers, GPS (5 cm accuracy), RGB, and depth cameras. Some robots in the swarm also feature trip-wire detection to counter mines like the "starfish." Fig. 1 provides an overview of the swarm's functionalities [4].

For real-time surface landmine detection, an RGB camera mounted on the robot is utilized, ensuring effective identification and processing of visual data [5].

Fig. 1. Details of demining robot. On the left, is the robot with the on-board GPS system and off-board GPS tower; on the right, a panoramic view of the robotic platform scanning the test field

As an example, a lightweight detection system has been introduced, capable of running on mobile devices operated by remote personnel at a safe distance from hazardous areas. The model's execution speed is dependent on the processing capabilities of the device, as it operates entirely within a web browser. The system architecture is illustrated in Fig. 2 [4].

The system demonstrates high flexibility, requiring only a Python backend to run on the robotic platform while connecting to a mobile camera. In this implementation, an iPhone 13 Pro serves as the primary sensor, utilizing its video camera to capture data as the robot navigates the environment. The backend streams video input from the camera, awaiting connection from the frontend interface.

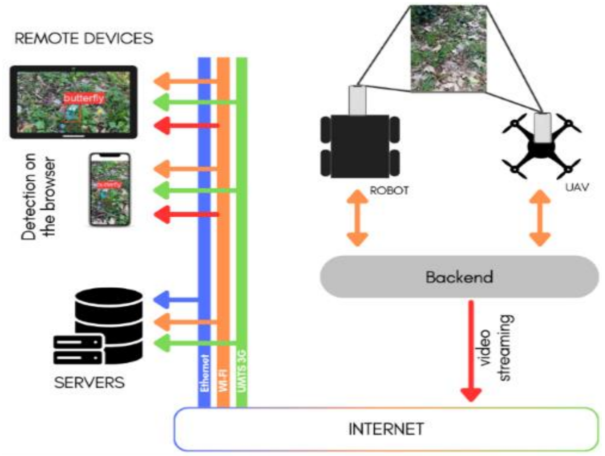


Fig. 2. The proposed system architecture; the components of the camera, backend, and frontend are independent of the moving vehicle used; this flexibility makes it possible to be used both on robot (left) and UAV (right) vehicles

Upon connection, the frontend retrieves YOLO (You Only Look Once) ONNX (Open Neural Network Exchange) weights from various sources and processes the incoming video stream using the model. The processed images, along with detection results, are then displayed on the user interface, as depicted in the tablet and smartphone visuals in the top-left section of Fig. 2.

Dataset creation and processing

To create comprehensive datasets for training and testing a real-time surface landmine detection system, data was gathered in diverse conditions to mimic real-world scenarios. The datasets cover various factors, including:

1) environment: grass and gravel terrains to capture surface variations;

2) weather: multiple conditions like cloudy, sunny, and shadowy settings, affecting image quality and landmine visibility;

3) obstacles: presence of bushes, branches, walls, trees, trunks, and rocks, which can obscure landmines.

Two open datasets have been used as an example. The datasets specifically built for surface landmine object class. First dataset uses scale models of Russian POM-2 and POM-3 surface mines. The second dataset uses model of PMA-2 "starfish" landmine. All landmines are illustrated in Fig. 3.

a b c

Fig. 3. Images of used landmines:
a – POM-2, b – POM-3, c – PMA-2 "starfish"

First dataset consists of 4485 images (88% are used for train set) with a valid set of 402 images where each image represents a mine (not only the mines illustrated above) that has been put under a certain environment and weather conditions and the test data set consisted of 249 images [7, 8]. Additional dataset details are presented in Table 1. The second dataset comprises 47 recorded videos, each with an average duration of 107 seconds, captured at a frame rate of 6 frames per second (FPS). Approximately 25% of the frames contain at least one landmine, resulting in 6,640 annotated frames out of a total of 29,109 frames in the dataset [4]. Additional dataset details are presented in Table 2.

Table 1 – **Data categories for the first dataset. Values were calculated from 4485 varying in resolution from 800px x 400px up to Full HD (1920px x 1080px)**

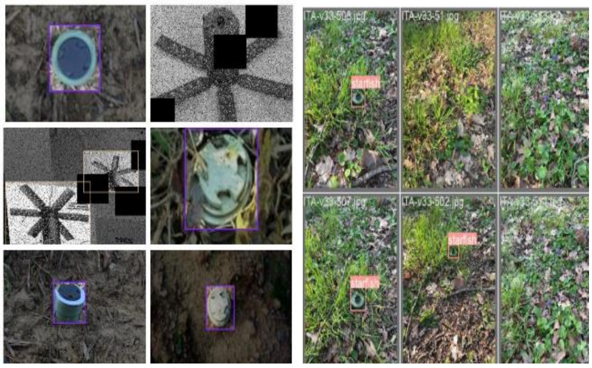
	Environment		Weather		
Split	**Grass**	**Gravel**	**Sunny**	**Shadow**	**Cloudy**
Train	2009	1892	2192	678	1031
Valid	296	106	164	97	141
Test	155	94	91	75	83

Table 2 – **Data categories. Values were calculated over the 47 ITA (Image Transformation Augmentation) videos (IID (Independent and Identically Distributed)), and 11 USA videos (OOD (Out of Distribution))**

	Environment		Weather		
Split	**Grass**	**Gravel**	**Sunny**	**Shadow**	**Cloudy**
Train	26	8	15	12	7
Valid	3	2	1	3	1
Test (IID)	4	2	2	3	2
Test (OOD)	11	0	8	1	2

Model selection and determination

The annotation process was conducted using the Computer Vision Annotation Tool (CVAT), a widely utilized framework for image annotation. Fig. 4 presents examples of annotated frames captured under various conditions. To meet the requirement for real-time processing in landmine detection, a single-stage object detection method was selected. Object detection approaches are generally categorized into single-stage and multi-stage methods. Multi-stage models, such as the R-CNN (Region-based Connected Neural Networks) family (R-CNN, Fast R-CNN, Faster R-CNN), first generate potential object regions before performing object detection within those regions [9, 10]. In contrast, single-stage models, such as YOLO, detect objects directly without a separate region proposal step [11, 12]. YOLOv8 was selected for its real-time performance and efficiency, crucial for landmine detection [13]. After conversion to ONNX, the models became lightweight (3MB for "nano" and 11MB for "small"), ensuring easy deployment on platforms like browsers, smartphones, and tablets. This compact size reduces computational load while maintaining accuracy. YOLOv8's strong performance with smaller annotated datasets made it ideal for efficient landmine detection.



a b

Fig. 4. Examples of annotated data using CVAT: a– for the first dataset; b – for the second dataset

AI-driven computer vision and multi-sensor robotics improve the efficiency and accuracy of explosive object detection. Using deep learning models like YOLOv8 with UGVs and UAVs enables real-time landmine detection in diverse environments [14]. Datasets reflecting different weather, terrain, and conditions enhance model reliability. Lightweight deployment on mobile devices ensures flexibility in hazardous areas, while advancements in AI, robotics, and aerial surveillance reduce risks and improve safety in demining operations, supporting global humanitarian efforts.

Experimental setup

To thoroughly evaluate the performance of the landmine detection system, a set of metrics was defined to measure precision, recall, and overall model effectiveness across varying conditions [15]. These metrics are essential for minimizing false negatives, as accurate detection of each landmine is critical for safety. For this particular case a few key metrics were selected:

$$P = \frac{TP}{TP + FP} \ ,$$

P – precision, proportion of true positive predictions relative to all positive predictions made by the model; a higher precision indicates fewer false positives; TP – true positive predictions; FP – false positive predictions;

$$R = \frac{TP}{TP + FN},$$

R – recall, the proportion of true positive detections out of all actual positive cases; essential for reducing the likelihood of missed landmines; FN – false negative predictions;

$$A = 2 * \frac{P * R}{P + R},$$

A – the weighted average of Precision and Recall, reflecting the overall accuracy of the model. YOLOv8 model training was performed using the composed dataset, which was collected and annotated specifically for this task. The training process included the following stages:

1) pre-trained model: the initial phase involved training on the “ImageNet” dataset, comprising RGB images and corresponding annotations across 1000 classes sourced from the internet. This stage is essential for learning fundamental image features such as colors, shapes, and general object structures;

2) initial fine-tuning: fine-tuning was conducted using the “SurfLandmine” dataset, which consists of RGB video recordings annotated with landmine instances under various environmental conditions in Italy. Video sequences were divided into individual frames and shuffled to ensure variability. The dataset includes a range of weather conditions, soil types, and surroundings, providing a comprehensive base for robust training;

3) validation: a designated subset of data was utilized to validate model performance at intervals during the training process, ensuring the system’s ability to generalize effectively to previously unseen data.

To accelerate the training process, distributed and parallel computing was applied.

Results

The YOLOv8 model's effectiveness in landmine detection was evaluated using both IID and OOD data. Performance results for YOLOv8-nano model are shown in the confusion matrix (Table 3) and summarized in Table 4.

Table 3 – **Confusion matrix for YOLOv8-nano**

Predicted\ Actual	POM-2	POM-3	Starfish	Environment
POM-2	384	0	0	18
POM-3	0	188	0	9
Starfish	0	0	166	5
Environment	81	67	90	0

Table 4 – **Summary table for YOLOv8-nano**

Class	Precision (P, %)	Recall (R, %)	Avg. accuracy (A, %)
POM-2	95.5	82.6	88.6
POM-3	95.4	73.7	82.8
Starfish	97	64.8	77.7
Environment	-	0	-

Results breakdown for YOLOv8-nano:

– POM-2 class: TP = 384 (POM-2 predicted as mine POM-2); FN = 81 (POM-2 predicted as environment); FP = 18 (Environment predicted as POM-2).

– POM-3 class: TP = 188 (POM-3 predicted as mine POM-3); FN = 67 (POM-3 predicted as environment); FP = 9 (Environment predicted as POM-3);

– Starfish class: TP = 166 (Starfish predicted as mine Starfish); FN = 90 (Starfish predicted as environment); FP = 5 (Environment predicted as Starfish).

Another model used for results evaluation was YOLOv8-small. The observations are collected in the confusion matrix in Table 5 and summarized in Table 6.

Results breakdown for YOLOv8-small:

– POM-2 class: TP = 395 (POM-2 predicted as mine POM-2); FN = 90 (POM-2 predicted as environment); FP = 9 (Environment predicted as POM-2).

– POM-3 class: TP = 182 (POM-3 predicted as mine POM-3); FN = 51 (POM-3 predicted as environment); FP = 7 (Environment predicted as POM-3);

– Starfish class: TP = 172 (Starfish predicted as mine Starfish); FN = 101 (Starfish predicted as environment); FP = 2 (Environment predicted as Starfish).

Table 5 – **Confusion matrix for YOLOv8-small**

Predicted\ Actual	POM-2	POM-3	Starfish	Environ-ment
POM-2	395	0	0	9
POM-3	0	182	0	7
Starfish	0	0	172	2
Environment	90	51	101	0

Table 6 – **Summary table for YOLOv8-small**

Class	Precision (P, %)	Recall (R, %)	Avg. accuracy (A, %)
POM-2	97.8	81.4	88.8
POM-3	96.3	78	86
Starfish	98.8	63	76.9
Environment	-	0	-

As shown in Table 4, the YOLOv8-nano model achieved high precision in detecting POM-2, POM-3, “starfish” mines with 95.5%, 95.4% and 97% respectively. However, it demonstrated lower precision for the "environment" class, where non-mine objects were often misclassified as threats. Despite the low false negative rates – a critical factor in mine detection – the model produced false positive rates of approximately 18% for POM-2, 26% for POM-3 and 35% for "starfish".

Table 6 indicates similar behavior from the YOLOv8-small model, with a slight reduction in the overall false positive rate. Precision values for POM-2, POM-3 and "starfish" reached 97.8%, 96.3% and 98.8% respectively. While false positives for POM-3 decreased compared to the nano model, they still present challenges for real-world deployment. A detailed evaluation of the model’s performance on the proposed datasets indicates that YOLOv8 models deliver strong recall and precision when operating within the training data distribution. Running at 2 FPS in a smartphone browser, the model demonstrates notable portability, with compact sizes of 3 MB (nano) and 11 MB (small), making it suitable for deployment on a wide range of devices. However, results highlight a significant distribution shift between IID and OOD data, emphasizing the composed dataset’s complexity and the challenge of object detection under unfamiliar conditions, as evidenced by a high false negative rate in OOD scenarios. These findings underscore the need for further model enhancement through targeted data augmentation, focused training on edge cases, and refined hyperparameter tuning to improve generalization.

Conclusions

This study introduces a novel real-time surface landmine detection system integrated into a demining robot. Operating at 2.6 frames per second, the system is lightweight, user-friendly, and accessible through web browsers and smartphones. Its high recall rate marks a substantial step forward in improving landmine detection capabilities. To the best of current knowledge, this is the first approach to surface landmine detection with a strong emphasis on operational speed, resulting in longer deployment durations compared to UAV-based methods, which are typically constrained by battery limitations.

A key feature of the system is its handling of false positives – an inherent challenge in detection tasks. Although the YOLOv8-nano and YOLOv8-small models exhibit elevated false positive rates, this conservative approach is justified in landmine scenarios. Alerts can be promptly reviewed by a human operator via smartphone, reducing the chance of missing real threats and enhancing the safety of both robotic platforms and nearby personnel.

References

1. Fedorenko G., Fesenko H. and Kharchenko V. Analysis of methods and development of the concept of guaranteed detection and recognition of explosive objects. *Innovative technologies and scientific solutions for industries.* 2022. No. 4(22). Pp. 20–31. DOI: https://doi.org/10.30837/ITSSI.2022.22.020.
2. Qiu Z., Guo H., Hu J., Jiang H., and Luo C. Joint Fusion and Detection via Deep Learning in UAV-Borne Multispectral Sensing of Scatterable Landmine. *Sensors.* 2023. Vol. 23. Iss. 12. Article number 5693. DOI: https://doi.org/10.3390/s23125693.
3. Levchenko D., and Podorozhniak A. Detection of explosive objects using artificial intelligence technologies. *Information Technologies: Science, Engineering, Technology, Education, Health: Proceedings of the XXXII International Scientific and Practical Conference MicroCAD-2024*, May 22-25, 2024– Kharkiv: NTU "KhPI" – P. 1406. URL: https://repository.kpi.kharkov.ua/handle/KhPI-Press/88551.
4. Vivoli E., Bertini M., Capineri L. Deep Learning-Based Real-Time Detection of Surface Landmines Using Optical Imaging. *Remote Sensing*. 2024. Vol. 16. Iss. 4. Article number 677. DOI: https://doi.org/10.3390/rs16040677.
5. Levchenko D., and Podorozhniak A. Detection of explosive objects using artificial intelligence and computer vision. *Modern Directions in the Development of Information and Communication Technologies and Control Systems*: *Proceedings of the Fourteenth Scientific and Technical Conference* (April 25-26), Vol. 1. – Baku: NGO AR; Kharkiv: NTU "KhPI", KhNURE; NAU "KhAI"; Žilina: UMŽ, 2024. – P. 63. URL: https://repository.kpi.kharkov.ua/handle/KhPI-Press/76906.
6. Kharchenko V., Kliushnikov I., Rucinski A., Fesenko H., and Illiashenko O. UAV Fleet as a Dependable Service for Smart Cities: Model-Based Assessment and Application. *Smart Cities*. 2022. Vol. 5. Iss. 3. Pp. 1151–1178. DOI: https://doi.org/10.3390/smartcities5030058.
7. Kunichik O. Landmine detection with a mobile application. *Eastern-European Journal of Enterprise Technologies*. 2024. Vol. 6. No. 2(132). Pp 6-13. DOI: https://doi.org/10.15587/1729-4061.2024.317103.
8. Kunichik O. Findmine Computer Vision Project, 2024. URL: https://universe.roboflow.com/oleksandr-kunichik-sugbr/findmine.
9. Ren S., He K., Girshick R., and Sun J. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence.* 2017. Vol. 39 (6). Pp. 1137–1149. DOI: https://doi.org/10.1109/TPAMI.2016.2577031.
10. Podorozhniak A., Liubchenko N., Sobol M., Onishchenko D. Usage of Mask R-CNN for automatic license plate recognition. *Advanced Information Systems*. 2023. Vol. 7. Iss. 3. Pp. 60–66. DOI: https://doi.org/10.20998/2522-9052.2023.1.09.

11. Redmon J., Divvala S., Girshick R., and Farhadi A. You Only Look Once: Unified, Real-Time Object Detection. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2016. Pp. 779–788. DOI: https://doi.org/10.1109/cvpr.2016.91.
12. Gavrylenko S., Wang Z. Pedestrian red light traffic recognition model based on YOLOv8 algorithm. *Advanced Information Systems*. 2025. Vol. 9. No. 2. Pp. 75–83. DOI: https://doi.org/10.20998/2522-9052.2025.2.10.
13. Mishchuk V., and Podorozhniak A. Analysis of Trade-Offs Between Accuracy and Speed of Real-Time Object Detectors for the Tasks of Explosive Ordnance Detection. *2024 IEEE 5th KhPI Week on Advanced Technology, KhPIWeek 2024*. Kharkiv, Ukraine. 2024. Pp. 1-5. doi: https://doi.org/10.1109/KHPIWEEK61434.2024.10878035.
14. Baur J., Steinberg G., Nikulin A., Chiu K. and de Smet T. S. Applying Deep Learning to Automate UAV-Based Detection of Scatterable Landmines. *Remote Sensing*. 2020. Vol. 12. Iss. 5. Article number 859. DOI: https://doi.org/10.3390/rs12050859.
15. Pochanin G., Capineri L., Bechtel T., Ruban V., Falorni P., Crawford F., Ogurtsova T., and Bossi L. Radar Systems for Landmine Detection: Invited Paper. *2020 IEEE Ukrainian Microwave Week (UkrMW)*. Kharkiv, Ukraine. 2020. Pp. 1118–1122. DOI: https://doi.org/10.1109/UkrMW49653.2020.9252789.

Received (Надійшла) 05.07.2025
Accepted for publication (Прийнята до друку) 27.08.2025

ВІДОМОСТІ ПРО АВТОРІВ / ABOUT THE AUTHORS

Левченко Денис Володимирович – магістр, магістр кафедри системного аналізу та інформаційно-аналітичних технологій, Національний технічний університет "Харківський політехнічний інститут", Харків, Україна;
Denys Levchenko – Master of Computer Science, Master of System analysis and information-analytical technologies department, National Technical University "Kharkiv Polytechnic Institute", Kharkiv, Ukraine;
e-mail: denys.levchenko@cs.khpi.edu.ua; ORCID Author ID: https://orcid.org/0009-0002-3258-0196.

Подорожняк Андрій Олексійович – кандидат технічних наук, доцент, професор кафедри комп'ютерної інженерії та програмування, Національний технічний університет "Харківський політехнічний інститут", Харків, Україна;
Andrii Podorozhniak – Candidate of Technical Sciences, Associate Professor, Professor of Computer Engineering and Programming Department, National Technical University "Kharkiv Polytechnic Institute", Kharkiv, Ukraine;
e-mail: andrii.podorozhniak@khpi.edu.ua; ORCID Author ID: https://orcid.org/0000-0002-6688-8407;
Scopus Author ID: https://www.scopus.com/authid/detail.uri?authorId=57202229410.

Любченко Наталія Юріївна – кандидат технічних наук, доцент, доцент кафедри системного аналізу та інформаційно-аналітичних технологій, Національний технічний університет "Харківський політехнічний інститут", Харків, Україна;
Nataliia Liubchenko – Candidate of Technical Sciences, Associate Professor, Associate Professor of System analysis and information-analytical technologies department, National Technical University "Kharkiv Polytechnic Institute", Ukraine;
e-mail: andrii.podorozhniak@khpi.edu.ua; ORCID Author ID: https://orcid.org/0000-0002-4575-4741;
Scopus Author ID: https://www.scopus.com/authid/detail.uri?authorId=57202232887.

Інструменти та методи виявлення вибухонебезпечних предметів з використанням штучного інтелекту та комп'ютерного бачення

Д. В. Левченко, А. О. Подорожняк, Н. Ю. Любченко

Анотація. У цьому дослідженні представлено детальний аналіз інструментів і методів, що використовуються, включно зі стратегіями збору даних, вибором моделі та архітектурою системи. Завдяки використанню технологій штучного інтелекту в режимі реального часу на роботизованих і повітряних платформах можливе досягнення прогресу в автоматизованому виявленні вибухонебезпечних предметів, що знижує ризики ручного розмінування та підвищує безпеку в уражених регіонах у всьому світі. **Актуальність**. Проблема виявлення вибухонебезпечних предметів залишається однією з найгостріших у сучасному світі та в Україні зокрема через зростання кількості збройних конфліктів і забруднення територій мінами та нерозірваними боєприпасами. Традиційні методи розмінування є трудомісткими, небезпечними, вимагають багато часу та не завжди є ефективними, що зумовлює необхідність впровадження інноваційних технологій на основі штучного інтелекту та комп'ютерного бачення. **Об'єкт дослідження.** Об'єктом дослідження є інтелектуальні інструменти та методи виявлення вибухонебезпечних предметів, зокрема пропонований прототип, що поєднує глибоке навчання (YOLOv8) та роботизовані платформи для реального часу. **Мета статті.** Метою статті є аналіз існуючих рішень, розробка та експериментальна перевірка ефективної, портативної системи для автоматизованого виявлення мін із використанням легких моделей глибокого навчання, здатної працювати на мобільних пристроях у різноманітних умовах середовища. **Результати дослідження.** У роботі використано, модернізовано та анотовано два спеціалізовані датасети, що охоплюють різні типи мін (POM-2, POM-3, PMA-2 "starfish") та різноманітні умови навколишнього середовища, типи ґрунтів, погодні фактори та наявність перешкод. Для пришвидшення тренування моделі штучного інтелекту застосовано розподілені та паралельні обчислення. Моделі YOLOv8-nano та YOLOv8-small продемонстрували високу точність (precision до 98,8%) і recall для основних класів мін, що підтверджено аналізом матриць плутанини та ключових метрик. Основна увага приділяється розробці та дослідженню прототипу системи для автоматизованого виявлення мін на основі глибокого навчання та комп'ютерного бачення, інтегрованої з роботизованими платформами та безпілотними літальними апаратами. Система забезпечує роботу у реальному часі (2–2,6 кадрів/с) на мобільних пристроях, має просту архітектуру та можливість інтеграції з роботизованими і безпілотними платформами. **Висновки**. Запропонована система є перспективною для гуманітарного розмінування завдяки високій точності, мобільності та простоті розгортання. Водночас результати експериментів вказують на необхідність подальшого вдосконалення моделей для підвищення стійкості до зміни умов середовища та зменшення кількості хибнопозитивних спрацювань. Впровадження таких рішень сприятиме підвищенню ефективності та безпеки розмінування у постконфліктних регіонах.

Ключові слова: безпілотні наземні операції, виявлення мін, штучний інтелект, обробка візуальних даних, комп'ютерне бачення, розподілені та паралельні обчислення.