IJARIIT
INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

ISSN: 2454-132X
Impact Factor: 6.078
(Volume 12, Issue 3 - V12I3-1180)
Available online at: https://www.ijariit.com

A Comparative Review of Deep Learning Methods for Landmine Detection from Vision Transformers to Ground-Penetrating Radar

Leidi M.Saleh Aouto
471217129@qu.edu.sa
Qassim University, Saudi Arabia

ABSTRACT

Landmines present a real problem around the world, causing injuries and a real threat to deminers' lives. Due to that, the search for safe and efficient demining methods has been a humanitarian priority for a long time. Traditional methods rely on physical probing and manual demining. However, these methods give high false-alarm rates, risks, costs, and are time-consuming. Thus, there is an urgent need to find innovative technologies and study their potential to give 100% efficient solution. This paper provides a comparative review of recent research in landmine detection and classification, focusing on the application of Artificial Intelligence and Deep Learning. We will evaluate the number of recently used deep learning methodologies, datasets and achieved performance results. This will help identify how Artificial Intelligence can succeed in solving the problems of demining operations. In this study, we will analyse the use of different algorithms with the overall goal of specifying the best findings to ensure high territory clearance, as well as specifying the challenges. This review provides important insights into the current state of the field, highlighting solutions that can enhance demining operations and improve detection accuracy.

Keywords: *Landmine Detection, Deep Learning, Computer Vision, Ground-Penetrating Radar (GPR), Thermal Imaging, Optical Imaging, Electromagnetic Induction (EMI), YOLO, Vision Transformer (ViT).*

1. INTRODUCTION

The process of clearing a field from landmines is a very complex and challenging operation that is still arising as a deadly problem these days. Landmines are grand-planted devices used to explode when a specific weight presses on them, for example a human, animal or vehicle passing the fields. The purpose of these devices is to create a line of protection that prevents the enemy from crossing into the protected area. They have been used during times of war, but these devices remain active for long periods of time and still carry the threat of fatal accidents. Because the method of distributing landmines is not organized and they have been hidden underground for a long time, the trace of their planting has disappeared due to natural factors. Thus, the threat they pose makes finding a safe solution to eradicate these mines an urgent and necessary matter. [1] [2] [3]

Traditional methods of mine clearance are unsafe and involve huge risks, potentially leading to unacceptable casualties, making this process critical. These methods include manual stimulation, metal detectors, or trained animals such as dogs. Also, they don't ensure high performance, they are extremely slow, also metal detectors often struggle with "clutter" leading to high error-rate, wasting the time and effort of deminers. [4] [5]

The use of new advanced hardware devices has transformed the concept of landmine detection and clearance. New demining strategies rely on multi-sensor fusion, data from Ground Penetrating Radar (GPR), thermal infrared sensors, and hyperspectral imaging to overcome the disadvantages of traditional methods. When they are integrated with autonomous platforms like Unmanned Aerial Vehicles (UAVs) or special ground robotics, these technologies give a high-resolution digital footprint of the terrain. This shift prohibits human operators from being exposed to the danger zone and provides the datasets needed for deep learning models to perform accurately. [2]

Artificial intelligence is a field of computer science that continues to expand, with the first concept emerging in the early 1950s. Nevertheless, the revolution of this field occurred in the 21st century, driven by the adoption of neural networks and machine learning. Artificial intelligence is the ability of machines to perform complex cognitive functions, examples include pattern recognition, language understanding, and decision-making, which were exclusive humans' tasks. It allows machine learning algorithms to analyze data and learn by experience. [6] [7]

Machine learning and deep learning were developed many decades ago; fields such as medicine, economics, and the military have been affected by the development of machine learning, which has helped them solve many problems.

In general, both fields leverage algorithms to learn from data examples, refine accuracy in predictions, and solve problems that require human cognition, yet they are varied fields of artificial intelligence. Machine learning enables systems to learn without explicit programming, meanwhile deep learning is considered to be a subset of machine learning, incorporating complex neural networks models that mimic the human brain. This difference gives a positive point for deep learning, which allows it to be proficient at analyzing unstructured data, making it more effective for solving difficult challenges. [8] These models can be applied to datasets generated using Ground Penetrating Radar (GPR), thermal sensors, or RGB cameras mounted on drones and transform raw sensor signals into actionable detection maps. [9]

There is a lot of researches that consider the solution of landmines detection problems, each uses different technology, in [10] researchers implemented the ViT model, the research in [11] utilized the YOLO family, [1] used three models specifically Retinanet, YOLOv5, and EfficientDet-D0, and paper in [4] evaluated six models including BinaryCNN, ResNet, ConvNeXt, ViT, OpenCLIP, InfMAE, [12] implemented ViT B/16 and VGG16 models. These papers represented high performance in developing a solution of landmines detection using AI models. Despite the high accuracy of these models, there is still a lack of consensus in terms of balancing speed and reliability in different environmental conditions.

The remainder of this paper presents a comparative review of 12 studies on deep learning techniques for landmine detection. For each study, sensor technology, dataset used, AI model architecture, and detection task are analyzed. Model performance is evaluated using metrics such as accuracy, recall, precision, and F1-score. Finally, the approaches are compared across three sensor categories; optical/thermal imaging, ground-penetrating radar (GPR), and electromagnetic induction (EMI), to assess their overall effectiveness and identify key challenges and future directions.

2. DEEP LEARNING APPROACHES FOR LANDMINE DETECTION: A TECHNOLOGY-BASED REVIEW

In this section, we will review 12 recently published papers from 2023 to 2025, dedicated to the Landmine Detection and Classification Field. The studies are divided based on the type of sensor technology used in each study, involving 3 technologies: Optical & Thermal Imaging, Ground-Penetrating Radar (GPR), Electromagnetic Induction (EMI), as shown in Table-1.

Table-1: Categorization of Reviewed Studies by Sensor Technology (Optical/Thermal, GPR, and EMI)

Section	Technology Used	Reference	Key Idea
2.1	**Optical & Thermal Imaging**	[2], [4], [10], [11], [14], [17], [18]	Detects surface or shallow mines using cameras (RGB, thermal) on drones/robots.
2.2	**Ground-Penetrating Radar (GPR)**	[9], [12], [15], [16]	Uses radar signals to see buried objects (both metal and plastic).
2.3	**Electromagnetic Induction (EMI)**	[13]	Detects metallic objects by sensing their electromagnetic signature.

2.1 Optical & Thermal Imaging-Based Detection

Optical and thermal imaging is a common technique for detecting landmines. These imaging systems are generally mounted on ground robots or drones and used to detect the visual and heat signatures of mines on the surface of the earth. These methods allow fast, no contact, and cost-effective detection, which makes them particularly suitable for large field surveys and immediate deployment. [11] [19]

Table-2 shows a comparison of seven studies, ones that utilize Optical and Thermal Imaging-based detection of landmines. The table here compares the sensor technology, the model used, the specific task or goal of the experiments, the dataset size and availability and most importantly the key results.

Table-2: Comparison of studies using Optical and Thermal Imaging for landmine detection.

Study	Publication Year	Sensor	Model	Task	Key Result	Dataset Size
Heuschmid et al. [2]	2025	Thermal (Drone)	MobileNetV3-Large	Binary classification (mine/no mine)	Accuracy: 96.14%, Precision: 97.03%, Recall: 94.23%	2,700 images (Tenorio-Tamayo dataset) **Public [21]**
Kim & Kwon [4]	2025	Long-Wave Infrared (Thermal) camera on UAV	ConvNeXt (with Attention-based Multiple Instance Learning & Transfer Learning)	Binary classification (image-level: landmine vs. no landmine)	*Best model from models trained with the duplicated train set:* **ConvNeXt** Precision: 0.991 ± 0.002 Recall: 1.000 ± 0.000 F1-score: 0.995 ± 0.001 *Best models from models trained with the inpainting-augmented train set:* **ConvNeXt** Precision: 0.996 ± 0.003 Recall: 1.000 ± 0.000 F1-score: 0.998 ± 0.001	659 images (Tenorio-Tamayo dataset) **Public [21]**

					ViT Precision: 1.000 ± 0.000 Recall: 0.928 ± 0.013 F1-score: 0.963 ± 0.007	
Parsayan et al. [10]	2025	Aerial IR	ViT (Transfer Learning)	Phase 1: Free zone vs. landmine Phase 2: surface landmines vs. deep landmines	*Phase 1:* Accuracy: 88%, F1-score: 87%, Recall: 96%, and an AUC: 0.86. *Phase 2:* Accuracy: 80%, F1-score: 80%, Recall: 82%, and an AUC: 0.91.	642 images (Tenorio-Tamayo dataset) **Public [21]**
Vivoli et al. [11]	2024	Optical Imaging (iPhone)	YOLOv8: nano vs. small	Surface landmines detection (PFM-1, PMA- 2)	YOLOv8-nano: Butterfly: Precision 72.16%, Recall 98%, FNR 2%, FPR 28% Starfish: Precision 55.63%, Recall 99%, FNR 1%, FPR 44% YOLOv8-small: Butterfly: Precision 75%, Recall 97%, FNR 3%, FPR 25% Starfish: Precision 57%, Recall 99%, FNR 1%, FPR 43%	29,109 frames (SULAND-Dataset) **Public [22]**
Qiu et al. [14]	2023	Multispectral (RGB + NIR)	YOLOv5 + Fusion Net	Occluded landmines	Precision 0.933, Recall 0.906, mAP@0.5 0.922, RMSE 0.13	789 image pairs **Private**
Lin & Wang [17]	2024	Low-resolution Thermal	Enhanced YOLOv8 + Cubic Spline	PFM-1 butterfly mine	78% of mAP50-95 (vs 55% for raw model) Precision 95.8% (vs 86.1% for	Custom small set
			Interpolation		raw model	**Private**
Bajic & Potočnik [18]	2023	Thermal (UAV)	YOLOv5 versions	11-class UXO detection / Edited single UXO class detection	*11-class UXO detection-best models:* YOLOv5s: Precision: **98.8%**, 88.5% of mAP@0.5:0.95 YOLOv5l: Precision: 98.4%, **90.5%** of mAP@0.5:0.95 **For all; Recall: 100%, 99.5% of mAP@0.5** *Edited single UXO class detection-best models:* YOLOv5s: Precision: **99.4%**, 90.5% of mAP@0.5:0.95 YOLOv5l: Precision: **99.4%**, 91.1% of mAP@0.5:0.95 YOLOv5x: Precision: 99.3%, **91.5%** of mAP@0.5:0.95 **For all; Recall: 100%,**	808 images (UXOTi_NPA) **Public [23]**

					99.5% of mAP@0.5	

The studies in Table-2 present high results. We notice that YOLO variants [11, 14, 18] were the most commonly used, achieving high recall (94–100%), but at the cost of medium false positives (25–44%). A key finding to mention here is that data augmentation in [11] and multi-spectral fusion used in [14] significantly boost performance, which emphasizes the importance of pre-processing strategies especially for challenging field conditions. Lightweight models such as MobileNetV3 and enhanced YOLOv8 variants assisted the ability of deployment on drones and smartphones in real-time.

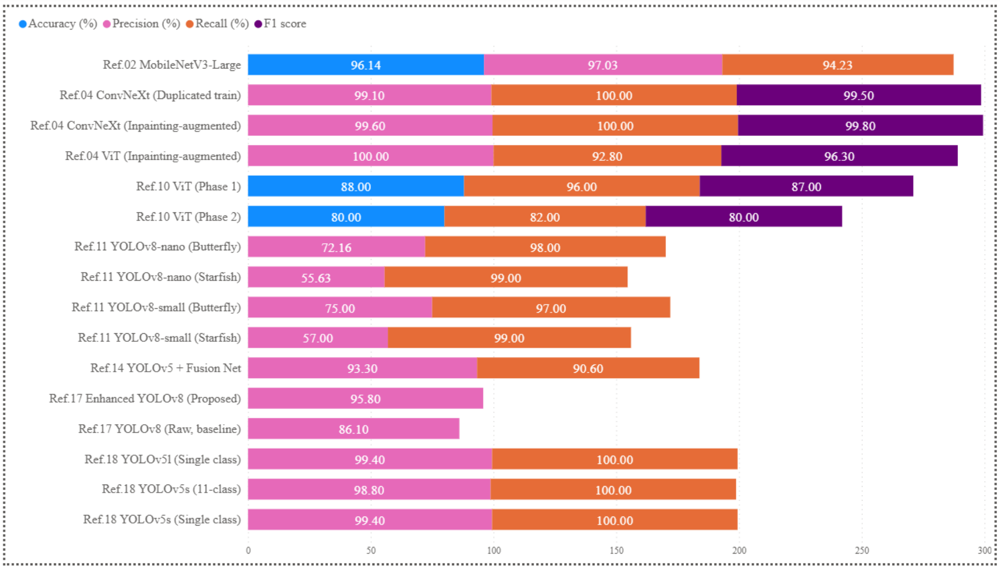

Chart -1: Accuracy, Precision, Recall, and F1-score of Optical & Thermal Imaging Models.

2.2 Ground-Penetrating Radar (GPR)-Based Detection

GPR is highly known technology for discovering buried threats of any type (metallic or plastic) it works by transmitting electromagnetic waves into the ground and the reflected signals coming from buried objects like landmines are analyzed, which appear as hyperbolic patterns in B-scan images. [12]

Table-3 displays a comparison of four studies; those used Ground-Penetrating Radar (GPR)-based detection of landmines. The table compares the sensor technology, the model used, the specific task or goal of the experiments, the dataset size and availability and most importantly the key results.

Table-3: Comparison of studies using Ground-Penetrating Radar (GPR) for landmine detection.

Study	Publication Year	Sensor/Data Source	Model	Task	Key Result	Dataset Size
Mochurad et al. [9]	2023	Real GPR (from public GitHub dataset)	Convolutional Autoencoder (Anomaly detection)	Binary classification (mine vs. no mine)	AUC = 97.83%	66 B-scans (with 8 object types) **Previously Public, Now Unavailable**
Kumar et al. [12]	2024	Simulated GPR (gprMax software)	ViT B/16 & VGG16 (Transfer Learning)	Binary classification (landmine vs. clutter)	*VGG16:* Accuracy: 96.9%, Precision: 100%, Recall: 89.5%, F1-score: 0.945 *ViT:* Accuracy: 94.8%, Precision: 100%, Recall: 93.7%, F1-score: 0.967	**960 simulated images** **Private**

Wang et al. [15]	2025	Hybrid (Simulation + Sand pit + Field)	Dual-Cascade CNN with Attention Mechanism	Hyperbola detection & target localization	Average Precision: 0.9261 (*vs* YOLOv9 0.8915) Average Recall: 0.9748 (*vs* YOLOv9 0.9303) Average F1-score: 0.9499 (*vs* YOLOv9 0.9099)	4,100 B-Scan images (4000 simulated, 100 real) **Partially available:** *Simulated data can be generated with gprMax; field data not publicly released*
Sezgin & Alpdemir [16]	2023	Real GPR (TUBITAK facility, Turkey)	Custom 3-layer CNN + pre-processing (constant / dynamic background removal, horizontal / wavelet filtering)	6-class classification (clutter + surrogate mines)	Accuracy: 99.9%, F1-score: 0.998 ± 0.003 (with pre-processing) *vs* Accuracy: 86.8%, F1-score: 0.782 ± 0.046 (raw data)	1,040 real GPR images **Private**

The studies in Table-3 emphasize that well-studied pre-processing techniques are the key to high GPR performance. Sezgin & Alpdemir [16] showed that after applying background removal and wavelet filtering, an increase in accuracy to approximately 100% was noticed. Similarly, Wang et al. [15] hired a dual-cascade network with attention mechanisms which outperformed YOLOv9 and Faster R-CNN. Mochurad et al. [9] trained an autoencoder only on mine-free soil scans, achieving 97.8% AUC, which is considered valuable for detecting unknown landmine types. Finally, Kumar et al. [12] compared ViT and VGG16 on simulated GPR data leading them to find that VGG16 model slightly outperformed the transformer (96.9% vs 94.8%), suggesting that for structured hyperbola patterns, traditional CNNs may still have an edge over transformers.

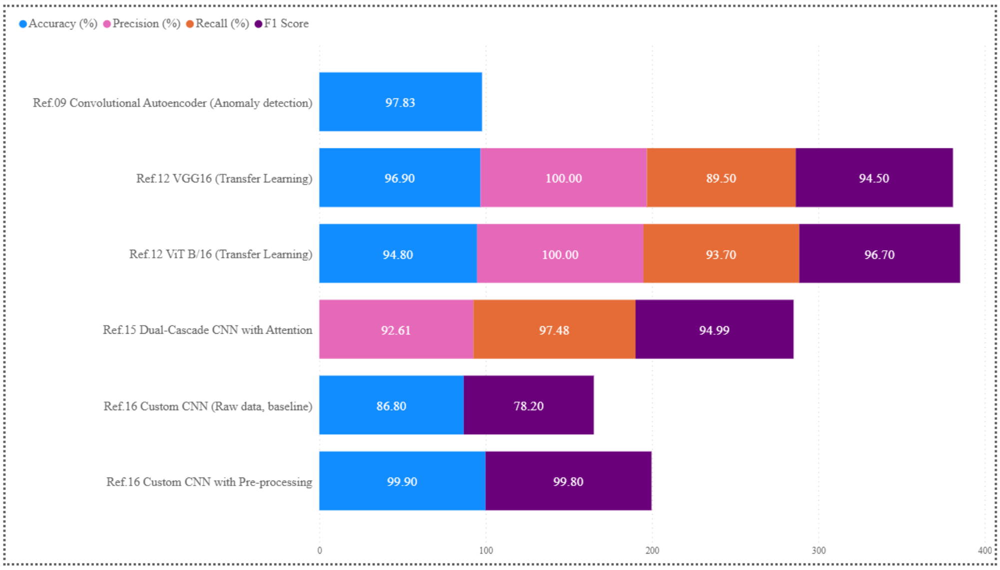

Chart -2: Accuracy, Precision, Recall, and F1-score of Ground-Penetrating Radar (GPR) Models.

2.3 Electromagnetic Induction (EMI) & Multi-Sensor Fusion

As demonstrated by Simic et al. [13], electromagnetic induction (EMI) sensors work by inducing eddy currents in metallic objects and measuring the resulting secondary magnetic field. This approach achieves high accuracy (98%) for detecting metal-cased landmines; however, it is inherently limited to conductive targets and cannot detect plastic mines by itself.

Most studies of the electromagnetic induction (EMI) response of a low-metal landmine buried in soil ignore any influence that the plastic casing may have on such response. In most cases such treatment is fine since only the metal parts of a landmine are expected to contribute to such a response. [20]

Table 4 displays a summary of the single study that used Electromagnetic Induction (EMI)-based detection of landmines. The table represents the sensor technology, the model used, the specific task or goal of the experiments, the dataset size and availability and most importantly the key results.

Table-4: Electromagnetic Induction (EMI)-Based Detection; Summary of the Single Reviewed Study.

Study	Publication Year	Sensor/Data Source	Model	Task	Key Result	Dataset Size
Simic et al. [13]	2024	Pulse Induction Metal Detector (VMF4) + EM tracking system	1D Convolutional Neural Network (1D-CNN)	Multiclass classification (2 landmine types vs 5 clutter types)	Accuracy: 98%; **Zero false negatives** (all landmines detected)	70 measurements (10 per object class) **Private**

For EMI-based detection only one study was reviewed, however it produced remarkable results. Simic et al. [13] used a 1D-CNN on magnetic polarizability tensor (MPT) features extracted from time-domain EMI data. A significant advancement was training the model entirely on simulated data (using scaling properties of Maxwell's equations) and checking with tangible metrics, narrowing the gap between simulations and reality. The model attained 98% total accuracy and, most importantly for safety, no false negatives whatsoever, which means all mines were identified correctly. Nevertheless, a failing is that EMI by itself does not succeed to detect mines containing minimal metal or plastic, which are increasingly common. Thus, it is recommended to combine EMI with GPR or thermal imaging.

3. KEY FINDINGS

Deep learning is very effective for landmine detection, as evidenced by the best results of all 12 studies. YOLO-based models achieved the best performance for optical and thermal imaging: [18] achieved 100% recall and 99.5% mAP for 11 UXO classes, [11] achieved 98-99% recall for surface mines using YOLOv8 on a smartphone, [4] achieved perfect recall (100%) with ConvNeXt on thermal images, and [2] proved that lightweight models like MobileNetV3 can achieve 96% accuracy on a drone. For GPR-based detection, pre-processing was the key to success: [16] improved accuracy from 87% to nearly 100% using filtering, [15] outperformed YOLOv9 with a dual-cascade attention network, and [9] achieved 98% AUC by training an autoencoder only on mine-free soil. For EMI, [13] achieved zero false negatives (100% detection of all landmines) with 98% accuracy, but this method cannot detect plastic mines alone. Overall, YOLO models excel at fast thermal detection, GPR with proper pre-processing reaches near-perfect accuracy for buried mines, and EMI offers perfect safety for metal targets.

4. KEY CHALLENGES AND LIMITATIONS

Despite high achieved accuracies (80–99%) across the reviewed studies, there are still critical challenges that remain before these methods can be deployed in real-world demining operations.

4.1 Small and Unbalanced Datasets

Many studies used small datasets. Some datasets were private, while others were public. Many datasets contained imbalance classes, such as only 64 free-zone images versus 591 mine images in [10], which increases the risk of overfitting and poor generalization.

4.2 False Positive vs. False Negative Trade-off

In the field of our review, missing a mine (false negative) can cause death, while false alarms (false positives) waste time and resources. [13] achieved zero false negatives but at the cost of some false positives. [10] had 96% sensitivity for mines but only 33% for free zones. [11] achieved 98% recall, but at the cost of 25–44% false positives. Balancing these measures remains difficult.

4.3 Poor Generalization to New Environments

The success of a model in certain terrains or conditions does not guarantee their success in other conditions. [11] tested their model on out-of-distribution (OOD) data from the USA and saw significant performance drops. [4] used image inpainting to show that models relied on spurious background features, not the mines themselves. [14] reported that occlusion by vegetation remains a major challenge.

4.4 Computational Cost vs. Real-Time Deployment

Accurate models like ViT [10] have 85.8 million parameters and require sophisticated GPUs that are not practical for drones or power-sensitive devices. On the other hand, lightweight models like YOLOv8-nano [11] and MobileNetV3 [2] allow for real-time deployment on smartphones and Raspberry Pi but may provide decreased results on accuracy.

4.5 No Standard Way to Compare Models

In our review paper, every study used a different dataset, different number of classes, and the evaluation metrics varied from one study to another. The (Tenorio-Tamayo dataset) [21] was reused across multiple studies [10], [4], [2]. Several studies published their datasets publicly: (SurfLandmine) [11] [22], (UXOTi_NPA) [18] [23], [9] (Guriarti 2, now unavailable). However, other studies used private datasets. It is still difficult to compare models fairly without standardized benchmarks.

5. FUTURE WORK AND RECOMMENDATIONS

This section provides insights into the future work and recommendations for developing and enhancing landmine detection and classification methods to be reliable and effective in real-world use.

5.1 Develop Public Datasets

Many studies used small, private datasets [13], [14], [17]. Only [18] released their self-collected data publicly. A large, diverse benchmark dataset that includes multiple terrains, weather conditions, and mine types is needed to enable fair comparison and assess generalization.

5.2 Explore Hybrid Sensor Fusion

Each sensor has limitations: thermal misses buried mines, GPR requires expertise, EMI cannot detect plastic-cased mines. [14] showed that fusing RGB and NIR improved recall from 0.848 to 0.906. Future systems should combine thermal, GPR, and EMI on a single drone or robot for strong large-area and deep detection.

5.3 Prioritize Lightweight Models for Edge Deployment

ViT [10] has 85.8M parameters which is not suitable for drones. YOLOv8-nano can run on smartphones [11], MobileNetV3 on drones [2] and improved YOLOv8 on Raspberry Pi [17]. Future works should consider models such as MobileNetV3, TinyViT and YOLOv8-nano with quantization and pruning.

5.4 Address the FP vs. FN Trade-off

Missed mines (False Negatives) can kill, meanwhile false alarms (False Positives) waste time. [13] achieved zero false negatives. [11] had 98% recall but 25–44% false positives. Future systems should use adjustable thresholds, cost-sensitive learning, ensemble voting using multiple models that must agree to raise an alarm.

6. CONCLUSION

In conclusion, this review shows that deep learning techniques achieved high accuracy (80-99%) across Optical and Thermal Imaging, GPR and EMI sensors for landmine detection. YOLO-family models offer best balance between speed and accuracy for real-time deployment whereas ViT and CNNs perform well on thermal and GPR data respectively. We observed that each sensor has strengths: optical/thermal is fast and low-cost for surface mines, GPR detects buried non- metallic mines, and EMI excels in metal-cased mines detection with zero false negatives. However, there are still arising obstacles that causes the mine detection process to be less effective than it could possibly be, including restricted private data, high false positive rates (25–44%), and the computational cost of heavy models. For the future progress public benchmark datasets, hybrid sensor fusion, and continued focus on the critical trade-off between safety (no missed mines) and efficiency (few false alarms) are required.

REFERENCES

[1] Barnawi A, Kumar K, Kumar N, Alzahrani B, Almansour A. A Deep Learning Approach for Landmines Detection Based on Airborne Magnetometry Imaging and Edge Computing Ahmed Barnawi1,*, Krishan Kumar2, Neeraj Kum. Computer Modeling in Engineering & Sciences (CMES). 2024 May 1;139(2).

[2] Heuschmid D, Wacker O, Zimmermann Y, Penava P, Buettner R. Advancements in landmine detection: Deep learning-based analysis with thermal drones. IEEE Access. 2025 May 21.

[3] Ściegienka P, Blachnik M. On the Development of a Neural Network Architecture for Magnetometer-Based UXO Classification. Applied Sciences. 2025 Jul 25;15(15):8274.

[4] Kim JH, Kwon GR. Image-level anti-personnel landmine detection using deep learning in long-wave infrared images. Applied Sciences. 2025 Aug 4;15(15):8613.

[5] Jafuno D, Mian A, Ginolhac G, Stelzenmuller N. Buried Object Classification from GPR Data by using Second Order Deep Learning Models. InIGARSS 2024-2024 IEEE International Geoscience and Remote Sensing Symposium 2024 Jul 7 (pp. 6513-6516). IEEE.

[6] Prasad A, Kumar AS, Sharma P, Irawati ID, DV C, Musirin IB, Abdullah HM. Artificial intelligence in computer science: An overview of current trends and future directions. Advances in artificial and human intelligence in the modern era. 2023:43-60.

[7] Mannuru NR, Shahriar S, Teel ZA, Wang T, Lund BD, Tijani S, Pohboon CO, Agbaji D, Alhassan J, Galley J, Kousari R. Artificial intelligence in developing countries: The impact of generative artificial intelligence (AI) technologies for development. Information development. 2025 Sep;41(3):1036-54.

[8] Sharifani K, Amini M. Machine learning and deep learning: A review of methods and applications. World Information Technology and Engineering Journal. 2023;10(07):3897-904.

[9] Mochurad LI, Savchyn V, Kravchenko O. Recognition of Explosive Devices Based on the Detectors Signal Using Machine Learning Methods. InIntelITSIS 2023 (pp. 249-260).

[10] Parsayan M, Parsayan A. Deep Learning for Humanitarian Landmine Detection in Aerial Remote Sensing Imagery Using Vision Transformers and Transfer Learning. In2025 International Conference on Artificial Intelligence, Computer, Data Sciences and Applications (ACDSA) 2025 Aug 7 (pp. 1-6). IEEE.

[11] Vivoli E, Bertini M, Capineri L. Deep learning-based real-time detection of surface landmines using optical imaging. Remote sensing. 2024 Feb 14;16(4):677.

[12] Kumar AA, Reddy MV, Agarwal A, Vishwamitra S, Chavan CP. Transfer Learning for Classification of GPR B- scan Images from Clutter using Vision Transformer and VGG-16. In2024 Second International Conference on Data Science and Information System (ICDSIS) 2024 May 17 (pp. 1-6). IEEE.

[13] Simic, M., Ambrus, D., & Bilas, V. (2023). Landmine Identification From Pulse Induction Metal Detector Data Using Machine Learning. IEEE Sensors Letters, 7(9), 1-4.

[14] Qiu, Z., Guo, H., Hu, J., Jiang, H., & Luo, C. (2023). Joint Fusion and Detection via Deep Learning in UAV-Borne Multispectral Sensing of Scatterable Landmine. Sensors, 23(12), 5693.

[15] Wang, H., Liu, Q., & Zhou, L. (2025). Underground target localization method for ground penetrating radar based on deep learning. Measurement, 253, 117647.

[16] Sezgin, M., & Alpdemir, M. N. (2023). GPR target Identification Using CNN based classifier. In 2023 IEEE International Conference on Advanced Systems and Engineering Technologies (IC_ASET) (pp. 1-6). IEEE.

[17] Lin, W., & Wang, Q. (n.d.). MineSeeker: A Novel Design for Detecting Explosive Mines Using Low-Resolution Thermal Imaging. Integem Inc., Cupertino, CA, USA.

[18] Bajic, M., & Potočnik, B. (2023). UAV Thermal Imaging for Unexploded Ordnance Detection by Using Deep Learning. Remote Sensing, 15(4), 967.

[19] Baur J, Steinberg G, Nikulin A, Chiu K, de Smet TS. Applying deep learning to automate UAV-based detection of scatterable landmines. Remote Sensing. 2020 Mar 6;12(5):859.

[20] Das, Y. (2008). Study of the influence of the plastic casing on the electromagnetic induction response of a buried landmine. SPIE Proceedings, Vol. 6953.

[21] H. A. Tenorio-Tamayo et al., “Dataset of thermographic images for the detection of buried landmines,” Data Brief, vol. 49, p. 109443, Aug. 2023.

[22] Vivoli, E. (2024). SULAND-Dataset: Surface Landmine Detection Dataset [GitHub repository]. GitHub. Accessed: May 15, 2026. Available: https://www.github.com/miccunifi/SULAND-Dataset

[23] Bajić, M., & Potočnik, B. (2023). UAV thermal imaging for unexploded ordnance detection by using deep learning. Remote Sensing, 15(4), 967. doi: 10.3390/rs15040967 Dataset available at: https://github.com/MilanBajicjr/UXOTi_NPA (Accessed: May 15, 2026)