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AI for ERW Detection in Clearance Operations - A Brief Review of the Current Research

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This literature review was produced as part of a wider research project for a Master's thesis at the University College London. The project is supervised by Benjamin Guedj (Associate Professor UCL; b.guedj@ucl.ac.uk; <https://bguedj.github.io/>).

Abstract

Today, 60 countries suffer from landmines and other unexploded ordnance, and more than 4,700 people were killed or injured by these explosives in 2022. At the same time, mine clearance is a lengthy and resource-intensive process. The areas to be searched for mines usually cover large regions, and skilled deminers, hardware, and funding are limited. Machine learning (ML) researchers have proposed several solutions to increase the efficiency and effectiveness of mine clearance.

This brief review of the current research aims to provide an overview of findings on the use of machine learning to support ERW detection in clearance operations. In particular, it aims to answer which input features are used in research to train ML algorithms (RQ1), which ML algorithms are used to predict the presence of ERW (RQ2), and which gaps in research exist on this topic (RQ3).

The review shows that studies on object detection, especially based on GPR and metal detector data, dominate the research while less than 10% of the research studies ML for ERW risk prediction. It also highlights the wide variety of input features used for ERW risk prediction algorithms. Furthermore, the review finds that SVMs and neural networks are the most studied ML algorithms to support ERW clearance. However, it also points out significant differences in ML techniques between the individual lines of research. Finally, the review highlights areas for future research. Most importantly, future research should focus on landmine risk prediction, work with real-world data and investigate performance improvements through input data fusion and incorporation of prior knowledge such as ERW patterns.

Introduction

Today, 60 countries suffer from landmines and other explosive remnants of war (ERW), and more than 4,700 people were killed or injured by these explosives in 2022 [1]. At the same time, clearance of ERW is a lengthy and resource-intensive process. The areas to be searched usually cover large regions, and skilled deminers, hardware, and funding are limited [2]. Machine learning (ML) researchers have proposed several solutions to increase the efficiency and effectiveness of ERW clearance. This literature review analyzes 100 eligible publications on AI systems to support ERW clearance which have been published between 1997 and 2024. In particular, the review answers three research questions:

RQ1: Which input features are used in research on ML models that support the detection of ERW in clearance operations?

RQ2: Which ML algorithms are analyzed in research on ML models that support the detection of ERW in clearance operations?

RQ3: What are the gaps in research on ML models that support the detection of ERW in clearance operations?

Method

The three research questions are answered based on an analysis of 100 eligible publications on the topic of ML for ERW detection in clearance operations. These studies are the result of a comprehensive literature search. The search follows a multi-step process that includes several screening steps to identify eligible studies (see Figure 1). It starts with a keyword search in seven databases, balancing sources focused on AI-related research and sources focused on peace/policy-related research. The keywords combine terms from the groups “explosive remnants” and “artificial intelligence” (see Table 1, Appendix). Both groups of keywords are linked with an “AND” operator to form a search string. All terms/synonyms within each group are combined with an “OR” operator. The search returns 1,558 results. All publications are then screened on the basis of their title and abstract and, in a second stage, on the basis of their full text. Each screening selects eligible studies based on the inclusion and exclusion criteria defined for the review (see Table 2, Appendix). Finally, the screening results in 100 eligible studies.

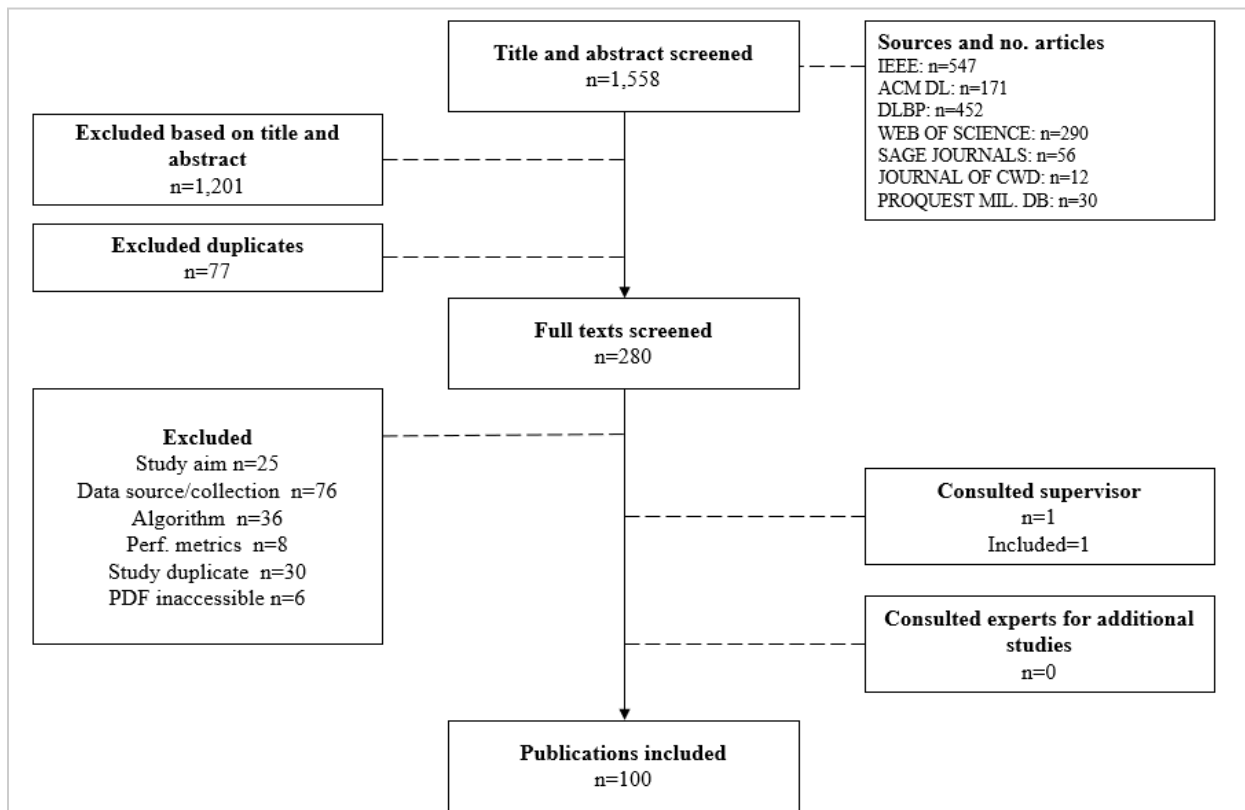


Figure 1: Flowchart of literature search and selection process

Results

The 100 eligible studies are analyzed in detail to answer the research questions of this review (see Table 3, Appendix).

RQ1: Input features. Research on AI systems for clearance operations can be grouped into two main streams (see Figure 2). A majority of the research focuses on object detection. This includes research on AI systems to detect ERW during clearance operations. In contrast, a minority of the research focuses on ERW risk prediction for a region of interest. Both streams use different input data for the predictions.

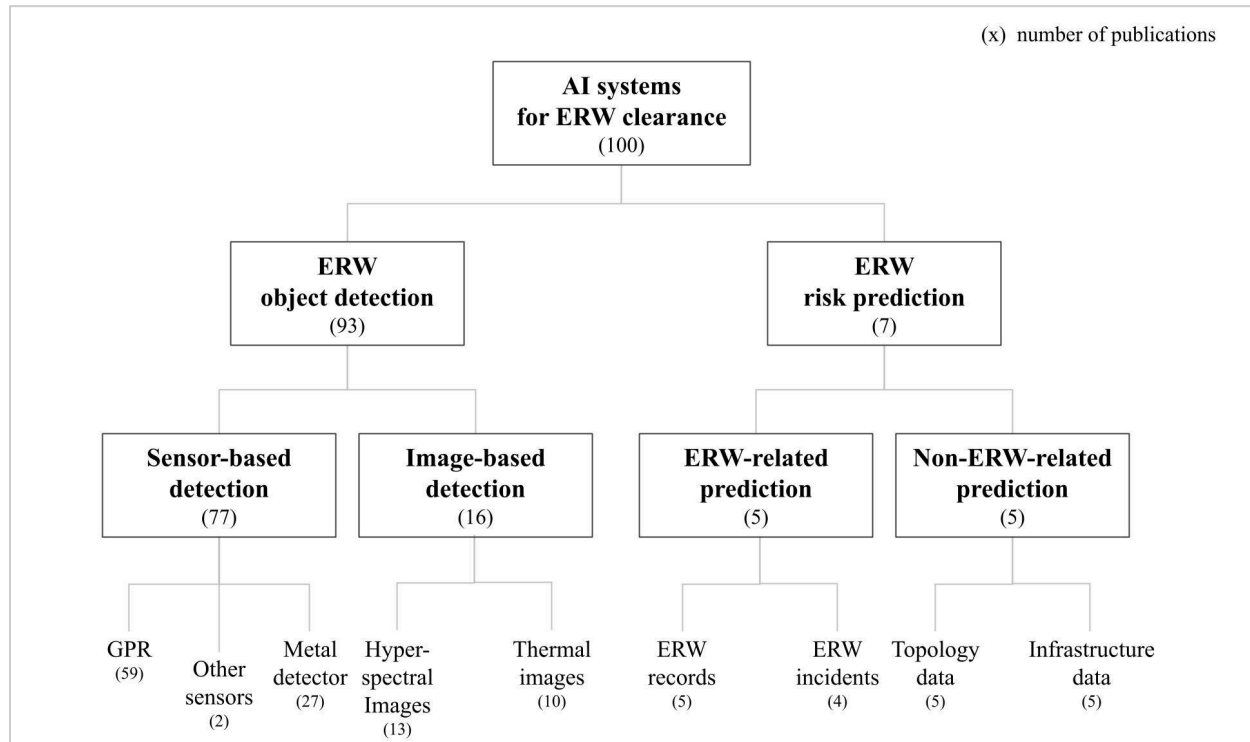


Figure 2: Research streams on AI systems to support ERW clearance

The first research stream focuses on object detection and includes 93 publications. These cover a wide range of input data types which can be grouped into sensor data, including data from ground penetrating radar (GPR), metal detectors and other sensors, and image data, including thermal and hyperspectral image data. Most of the research (59 publications) using sensor data focuses on GPR data. However, research on GPR only started in 2001 when Agarwal et al. published their paper on sensor fusion of GPR and metal detector data [3]. There is less research on ML techniques with metal detector data (27 publications). These authors analyze different types of metal detectors such as magnetometers or electromagnetic induction sensors (EMI). Also, Plett et al. leverage data from a microwave sensor which is a cheaper alternative to a GPR sensor [4]. Further, Ali et al. analyze ML techniques with input data from a contact pressure sensor [5]. In contrast to sensor data, only 16 studies use image data. 13 authors use hyperspectral image data, such as Bolton and Gader who work with airborne image data with 70 spectral responses [6]. However, other publications only use RGB image data such as Baur et al. who use

RGB image data acquired by drones [7]. Another 10 researchers use infrared or thermal image data to detect ERW. The thermal image data is used to detect both buried landmines and surface UXO [8], [9].

In addition, sensor fusion for ERW object detection with ML is analyzed by 14 authors. Most of them (10 publications) combine GPR and metal detector data to improve ERW object detection results, for example [3]. However, two publications combine EMI and magnetometer data to improve detection performance [10], [11]. Also, two further publications focus on sensor fusion of different image sensors such as RGB and thermal image data [12], [13].

The second stream of research focuses on ERW risk prediction for a region of interest and includes 7 publications. These authors use input data that can be divided into ERW-related and non-ERW-related data. The ERW-related data includes information from ERW records as well as data from ERW incidents in the region of interest. For example, Alegria et al. use only landmine incident data to train their model [14]. Riese et al. also use several ERW-related features, such as the distance to the nearest minefield, the distance to the confrontation line and the distance to the nearest recorded mine accident to train their model [15]. The non-ERW-related data includes various information on the topology and infrastructure of the region of interest. Topological features contain information on elevation, incline, land use, forests, rivers, animal density, soil texture, temperature, rainfall and visibility [15], [16], [17], [18], [19]. In addition, infrastructure features contain information about roads, railways, airfields, seaports, bridges, cities, buildings, financial institutions, schools, borders, telecommunication lines, power lines, oil lines, orchards, bunkers, trenches, and shelters [15], [16], [17], [18], [19]. Interestingly, most publications on ERW risk prediction use a combination of ERW-related and non-ERW-related data.

Finally, the analysis of other training data and study characteristics reveals significant qualitative differences between the publications (see Table 3, Appendix). Only eight publications use real-world data collected from ERW clearance operations, for example Rafique et al. who use data from a demining operation in Colombia [16]. However, 92 publications use test field data to train and test the ML models. Further, 87 publications focus on predictions for landmine detection, of which 44 include anti-tank (AT) landmines, 36 include anti-personnel (AP) landmines and 32 do not specify the type of landmine used. 13 publications focus on predictions for other UXO such as unexploded ammunition. Also, two publications focus on predictions for improvised explosive devices (IED) [20], [21]. Of the ERW analyzed, 58 publications include metallic ERW, while minimal-metallic (30) and plastic (28) ERW are less frequently analyzed. Furthermore, 64 publications include buried objects in the analysis and 41 publications test their ML system for different soil types.

RQ2: ML algorithms. Based on these input features, a variety of ML models are developed and evaluated in the eligible studies. In total, 30 different types of ML algorithms are used (see Figure 3). A majority of these algorithms can be categorized into five groups which are analyzed in at least ten publications. These groups are (convolutional) neural networks (39 publications), support vector machines (27 publications), linear or logistic regression (twelve publications), hidden markov models (HMM) (eleven publications), and tree-based algorithms (10 publications). However, a detailed analysis of ML techniques and performance requires an analysis of each research stream to ensure comparability.

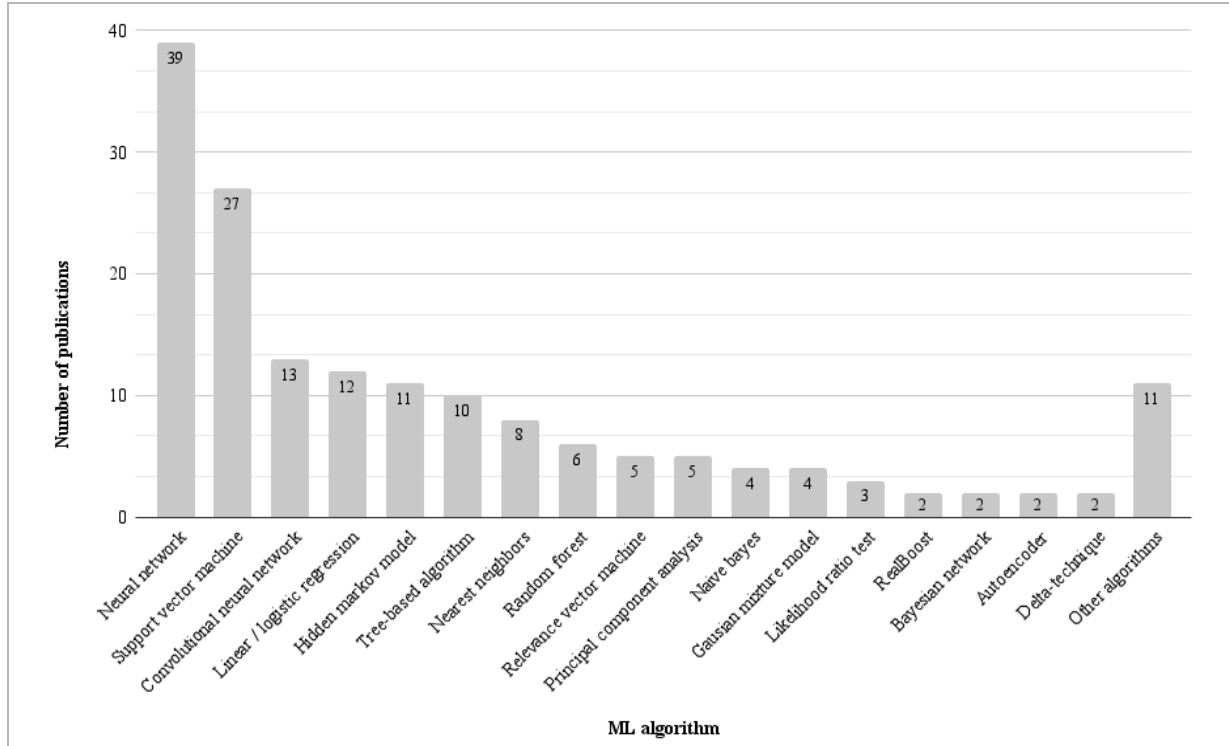


Figure 3: ML algorithms studied in research on AI systems for ERW clearance

The research stream on object detection from GPR data mostly uses SVMs (19 publications), neural networks (16 publications) and hidden markov models (ten publications) to detect ERW (see Figure 4, Appendix). These studies find that SVMs perform well in detecting different types of ERW from GPR data [22], [23], [24]. Also, they show that this technique can be applied for real-time detection [25]. In addition, some authors find that the performance can be improved with feature extraction [26]. In addition, 16 studies analyze the use of neural networks for ERW detection from GPR data. They find that neural networks outperform simpler techniques such as linear regressions [27]. Among them, two authors work with autoencoders to reconstruct the surface response and detect ERWs as anomalies [28], [29]. Also, seven authors use convolutional neural networks (CNN) to detect landmines from GPR data, for example [30]. Research also finds that hidden markov models perform well for ERW detection from GPR data and can generalize between sites [31], [32]. In particular, four publications find that an ensemble of HMMs performs better than a single HMM [33], [34], [35], [36].

In contrast, the research stream on object detection from metal detector data mainly analyzes neural networks (14 publications) (see Figure 5, Appendix). These authors find that neural networks perform well for ERW detection from metal detector data and can generalize between different test sites [37], [38], [39]. Also, researchers find that a neural network outperforms an SVM for ERW detection from metal detector data [40], [41]. Yet, Bray and Link show that a random forest model can outperform a neural network for this task [40].

Most publications of the research stream on object detection from image data use CNN models (6 publications) (see Figure 6, Appendix). The authors report high performance with detection rates of up to 90% [7], [42]. Also, pre-trained CNNs are found to perform well in this task [9], [43]. Yet, Silva et al. find that a simpler SVM can outperform a CNN for landmine detection from image data [44]. In addition,

Thomas and Cathcart propose an extension to image-based algorithms by incorporating pattern information from ERW to reduce the false alarm rate of predictions [45].

The research stream on landmine risk prediction mainly focuses on fundamental ML techniques such as SVMs, tree-based and nearest neighbors models (see Figure 7, Appendix). For example, Rafique et al. compare a logistic regression model with an SVM. They find that the SVM outperforms the logistic regression and generalizes better across different regions [16]. Further, Saliba et al. compare an SVM with a random forest and a XGBoost model and find that the random forest model performs best [18]. The other publications in this research stream analyze neural networks, tree-based models, nearest neighbors models, PCA and naive bayes approaches. However, they all focus on a single ML technique and therefore cannot provide a meaningful performance comparison [14], [15], [17], [19], [46].

RQ3: Research gaps. Finally, the analysis of the eligible publications reveals several gaps in current research and suggests three main areas for future research. First, the underrepresentation of publications on ERW risk prediction highlights the need for further research in this area. This research should aim to identify the most relevant input features for ERW risk prediction. It should also continue to compare different ML techniques for the prediction, as this has only been done by two publications [16], [18]. Second, future research should extend the work with real-world data from ERW clearance missions. In particular, research on ERW object detection rarely uses real-world data. The current dominance of test field data may be a reason for conflicting results and a lack of generalization. Third, future research should explore novel approaches to improve performance. In particular, future research should analyze the combination of different input data types, such as sensor-generated GPR and airborne image data. It should also analyze the use of landmine risk predictions as prior knowledge for object detection algorithms. In addition, future research should investigate the extension of algorithms with ERW pattern information for object detection and risk prediction, as introduced by Thomas and Cathcart [45].

Conclusions

The literature review analyzes input features, ML algorithms and gaps in current research on AI systems to support ERW clearance operations. It highlights the dominance of research on object detection, particularly based on GPR and metal detector data. It also highlights the wide variety of input features used for ERW risk prediction algorithms. Furthermore, the review finds that SVMs and neural networks are the most studied ML algorithms to support ERW clearance. However, it also points to significant differences in ML techniques between the individual lines of research. Finally, the review highlights areas for future research. Most importantly, future research should focus on landmine risk prediction, work with real-world data and investigate performance improvements through input data fusion and incorporation of prior knowledge such as ERW patterns.

Appendix

Group	Synonymous of groups of keywords
Explosive remnants	<ul style="list-style-type: none"> • Landmine, land mine, acoustic mine, antipersonnel, claymore mine, ground mine, magnetic mine, pressure mine, booby trap • Explosive remnants, unexploded ordnance, UXO, ERW, EO • Demining, de-mining, Mine clearance, mine detection, mine action
Artificial intelligence	<ul style="list-style-type: none"> • AI, artificial intelligence • ML, machine learning • Deep learning, neural network, ANN, DNN • RL, reinforcement learning • Advanced analytics • Supervised learning, Unsupervised learning • Prediction • Pattern recognition • Probability, probabilistic, Bayes, Bayesian • SVM, Support Vector Machine, Logistic Regression, Decision Tree, Random Forest

Table 1: Search terms and synonyms for literature search

Type	Criteria
Inclusion	Studies aiming to improve detection of land mines or explosives in post-conflict territories
	Studies aiming to predict the location of such land mines or explosives
	Studies using supervised machine learning or advanced analytics technologies to achieve its goals
	Studies that use real-world data sets
	Studies published in peer-reviewed journals
	Studies written in English language
Exclusion	Studies aiming to detect other items which are not explosive remnants in post-conflict territories or naval mines
	Studies not predicting location but focusing on other tasks, e.g., segmentation
	Studies focusing on non-ML technology , e.g., robotics or rule-based systems
	Studies using unsupervised learning techniques only
	Studies not been peer-reviewed or published in scientific journals
	Studies written in other languages than English

Table 2: Selection criteria for literature search

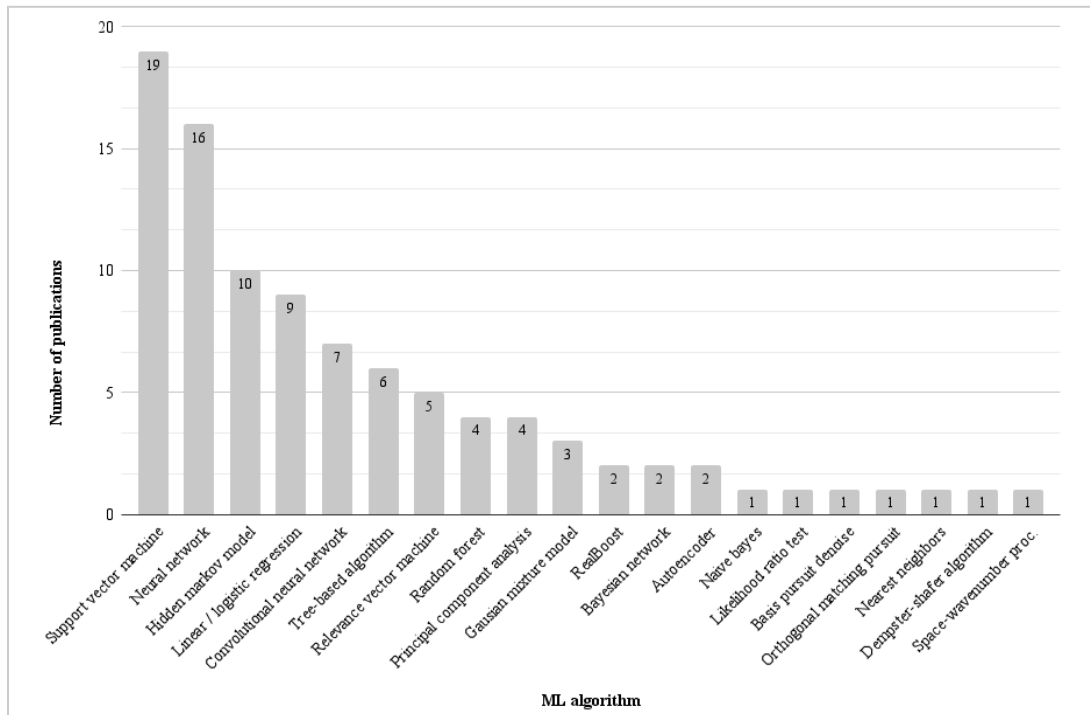


Figure 4: ML algorithms studied in research on ERW object detection from GPR data

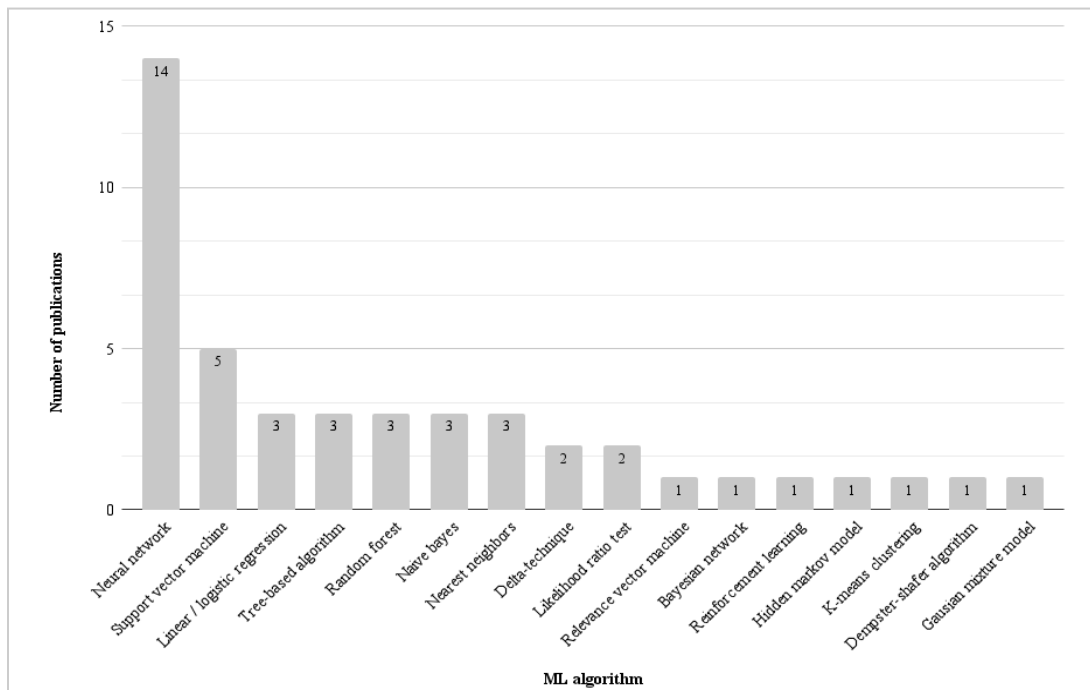


Figure 5: ML algorithms studied in research on ERW object detection from metal detector data

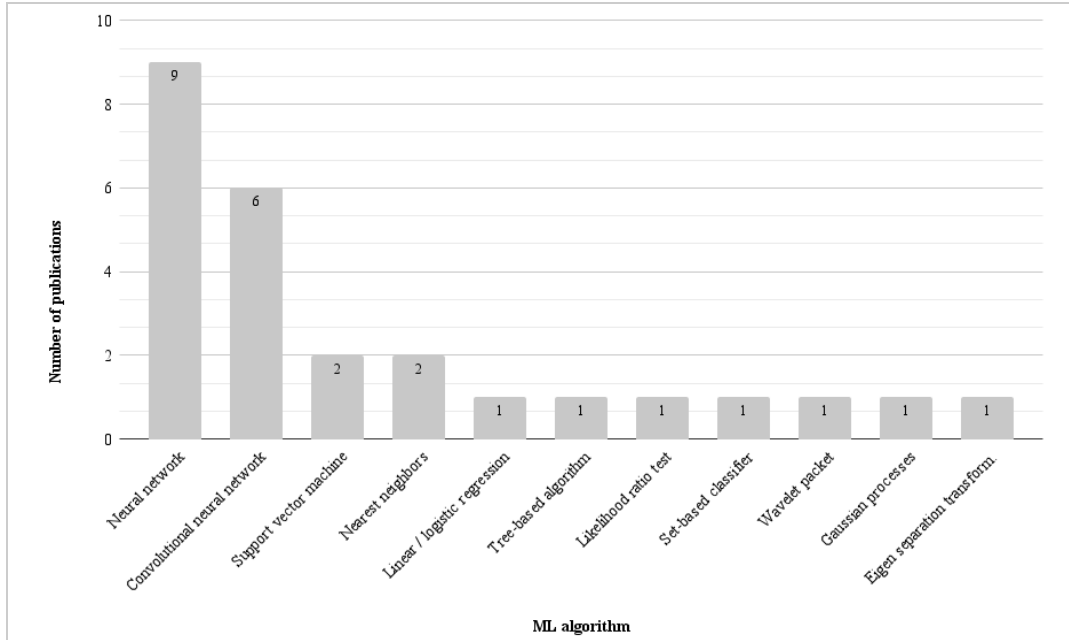


Figure 6: ML algorithms studied in research on ERW object detection from image data

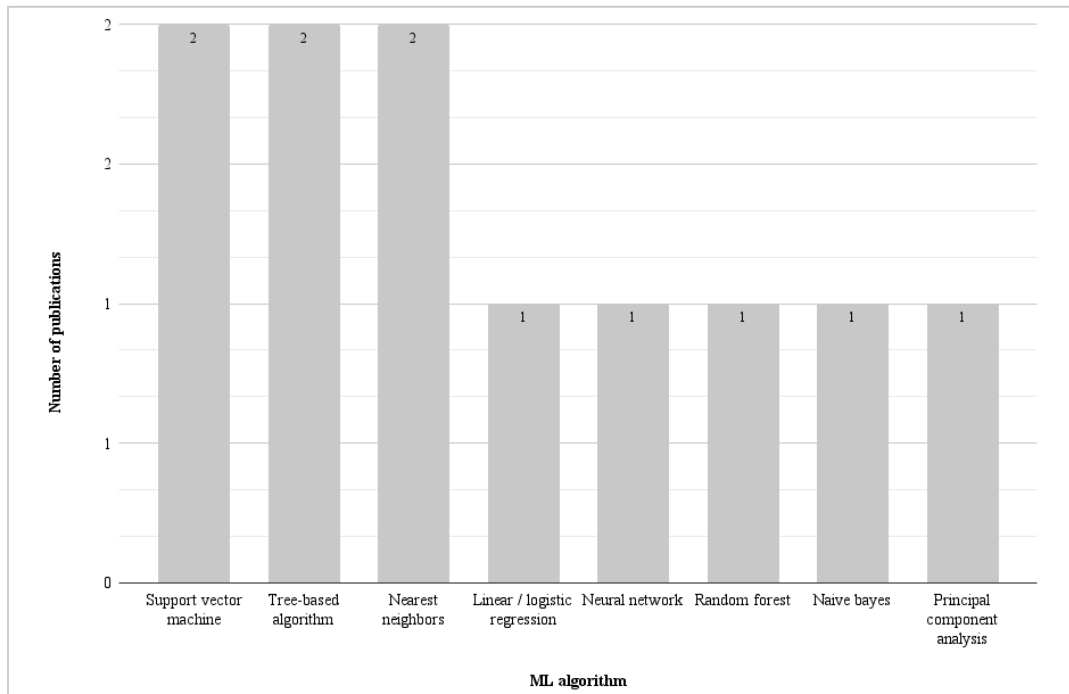


Figure 7: ML algorithms studied in research on ERW risk prediction

Table 3: Analysis of eligible publications

Year	Source	Study aim	Data acquisition	Acquisition device	Specific field conditions	ERW types	ERW material	Input features	AI algorithm	Result metrics	Key findings for literature review
1999	H. Abdelbaki, E. Gelenbe, T. Kocak, and S. E. El-Khamy, "Random neural network filter for land mine detection," in Proceedings of the Sixteenth National Radio Science Conference. NRSC'99 (IEEE Cat. No.99EX249), IEEE, 1999, pp. C431-C4310.	object detection	test field	handheld device	different soil types	landmine	not specified	metal detector, electro magnetic induction	neural network, delta-technique	ROC, detection rate, false alarm rate	NN filter for landmine detection from EMI works well in testing
2001	S. Agarwal, V. S. Chander, P. P. Palit, R. J. Stanley, and O. R. Mitchell, "Sensor fusion for hand-held multi-sensor landmine detection," in PROCEEDINGS OF THE SOCIETY OF PHOTO-OPTICAL INSTRUMENTATION ENGINEERS (SPIE), vol. 4394. 2001, pp. 991-1002.	object detection, sensor fusion	test field	handheld device	different soil types	AP landmine, AT landmine, landmine	metal, plastic	ground penetrating radar, metal detector	neural network, dempster-shafer algorithm	ROC, detection rate, false alarm rate	Feature level fusion performs best for fusion of GPR and metal detector data
2011	A. C. Alegria, H. Sahli, and E. Zimanyi, "Application of density analysis for landmine risk mapping," in IEEE International Conference on Spatial Data Mining and Geographical Knowledge Services, ICSDM 2011, Fuzhou, China, June 29 - July 1, 2011, IEEE, Jun. 2011, pp. 223-228.	risk prediction	real-world	not specified		landmine	not specified	ERW incident data	nearest neighbors, kernel density estimation		Landmine risk map based on only mine incidents performs well
2017	H. F. M. Ali, A. M. R. F. El-Bab, Z. Zyada, and S. M. Megahed, "Estimation of landmine characteristics in sandy desert using neural networks," Neural Comput. Appl., vol. 28, no. 7, pp. 1801-1815, 2017.	object detection	test field	vehicle mounted	buried	AP landmine, AT landmine, landmine	not specified	contact pressure distribution	neural network	detection rate, false alarm rate	Landmine detection via Contact pressure distribution can be improved with NN
2000	B. A. Baertlein and W. J. Liao, "Wavelet-based higher-order neural networks for mine detection in thermal IR imagery," in PROCEEDINGS OF THE SOCIETY OF PHOTO-OPTICAL INSTRUMENTATION ENGINEERS (SPIE), vol. 4038. 2000, pp. 168-178.	object detection	test field	not specified		AT landmine, landmine	metal, minimal-metal, plastic	image data , thermal images	neural network, wavelet packet decomposition	ROC, detection rate, false alarm rate	Wavelet-based NN performs well for landmine detection in thermal IR imagery
2010	M. Bajic, "The Advanced Intelligence Decision Support System for the Assessment of Mine-suspected Areas," The Journal of Conventional Weapons Destruction, vol. 14, no. 3, p. 28, 2010.	risk prediction	real-world	helicopter, satellite		landmine	not specified	image data , hyperspectral images, ERW incident data, ERW records, infrastructure data, topology data	principal component analysis, other algorithm	land reclassified	ML system with based on minefield records and spatial and airborne data achieves a cost-benefit ratio compared to that of other systems aiming to exclude areas of more than 140:1.
2022	A. Barnawi, N. Kumar, I. Budhiraja, K. Kumar, A. Almansour, and B. A. Alzahrani, "Deep reinforcement learning based trajectory optimization for magnetometer-mounted UAV to landmine detection," Comput. Commun., vol. 195, no. C, pp. 441-450, Nov. 2022.	object detection, search route optimization	test field	UAV / drone		landmine	not specified	metal detector, magnetometer	neural network, reinforcement learning	detection rate	Deep reinforcement learning supports trajectory optimization for magnetometer-mounted UAV
2021	J. Baur, G. Steinberg, A. Nikulin, K. Chiu, and T. de Smet, "How to Implement Drones and Machine Learning to Reduce Time, Costs, and Dangers Associated with Landmine Detection," The Journal of Conventional Weapons Destruction, vol. 25, no. 1, p. 29, 2021.	object detection	test field	UAV / drone		AP landmine, landmine	plastic	image data , hyperspectral images	neural network, convolutional neural network	detection rate, F1 score	CNN on UAV-based minefield data produces a model that can identify the PFM-1 mine with over 90% accuracy and can provide maps with mine locations
2020	J. Baur, G. Steinberg, A. Nikulin, K. Chiu, and T. S. de Smet, "Applying Deep Learning to Automate UAV-Based Detection of Scatterable Landmines," Remote. Sens., vol. 12, no. 5, p. 859, 2020.	object detection	test field	UAV / drone	different soil types	AP landmine, landmine	plastic	image data , thermal images, hyperspectral images	neural network, convolutional neural network	precision	UAV image data with NN achieves over 70% accuracy in mine detection
2014	L. E. Besaw and P. J. Stimac, "Deep Learning Algorithms for Detecting Explosive Hazards in Ground Penetrating Radar Data," in DETECTION AND SENSING OF MINES, EXPLOSIVE OBJECTS, AND OBSCURED TARGETS XIX, S. S. Bishop and J. C. Isaacs, Eds., in Proceedings of SPIE, vol. 9072. 2014. doi: 10.1117/12.2052592.	object detection	test field	handheld device	different soil types, buried	AP landmine, AT landmine, landmine	not specified	ground penetrating radar	neural network	ROC, detection rate, false alarm rate	NN can be taught to reconstruct background GPR data to detect anomalies as landmines

Year	Source	Study aim	Data acquisition	Acquisition device	Specific field conditions	ERW types	ERW material	Input features	AI algorithm	Result metrics	Key findings for literature review
2021	P. Bestagini, F. Lombardi, M. Lualdi, F. Picetti, and S. Tubaro, "Landmine Detection Using Autoencoders on Multi-polarization GPR Volumetric Data," IEEE Trans. Geosci. Remote Sens., vol. abs/1810.01316, no. 1, pp. 182–195, Jan. 2021.	object detection	test field	handheld device	different soil types, buried	AP landmine, AT landmine, landmine, other UXO	metal, minimal-metal, plastic	ground penetrating radar	neural network, convolutional neural network, autoencoder	AUC, ROC, detection rate, false alarm rate	Autoencoders can successfully be trained to detect landmines from GPR data with an AUC of 98%
2014	A. Bijamov, J. P. Fernández, B. E. Barrowes, I. Shamatava, K. O'Neill, and F. Shubitidze, "Camp Butner Live-Site UXO Classification Using Hierarchical Clustering and Gaussian Mixture Modeling," IEEE Trans. Geosci. Remote Sens., vol. 52, no. 8, pp. 5218–5229, 2014.	object detection	test field	not specified		other UXO	not specified	metal detector, electro magnetic induction	gaussian mixture model	false alarm rate	Gaussian Mixture Models can identify UXO correctly while minimizing FAR
2007	J. Bolton and P. D. Gader, "Application of random set-based clustering to landmine detection with hyperspectral imagery," in IEEE International Geoscience & Remote Sensing Symposium, IGARSS 2007, July 23-28, 2007, Barcelona, Spain, Proceedings, IEEE, 2007, pp. 2022–2025.	object detection	test field	airplane	buried	landmine	not specified	image data , thermal images, hyperspectral images	set-based classifier, nearest neighbors	ROC, detection rate, false alarm rate	Set-based clustering outperforms kNN for landmine detection
2015	M. P. Bray and C. A. Link, "Learning Machine Identification of Ferromagnetic UXO Using Magnetometry," IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens., vol. 8, no. 2, pp. 835–844, 2015.	object detection	test field	handheld device		other UXO	metal	metal detector, magnetometer	support vector machine, neural network, tree-based algorithm, random forest	detection rate, false alarm rate	Random Forest outperforms SVM and NN for landmine detection from EMI
2008	T. C. T. Chan, H. C. So, and K. C. Ho, "Fast communication: Generalized two-sided linear prediction approach for land mine detection," Signal Processing, vol. 88, no. 4, pp. 1053–1060, Apr. 2008.	object detection	test field	not specified	buried	AP landmine, landmine	minimal-metal	ground penetrating radar	linear / logistic regression	false alarm rate	Two-sided linear prediction can be trained to suppress ground reflection from GPR
2002	J. Cheng and E. L. Miller, "Model-based principal component techniques for detection of buried landmines in multiframe synthetic aperture radar images," in IEEE International Geoscience and Remote Sensing Symposium, IGARSS 2002, Toronto, Ontario, Canada, 24-28 June 2002, IEEE, 2002, pp. 334–336.	object detection	test field	not specified	buried	AT landmine, landmine	metal	ground penetrating radar	principal component analysis	ROC, detection rate, false alarm rate	Model-based analysis of sensor location with PCA improves landmine detection from GPR
2002	L. M. Collins, Y. Zhang, and L. Carin, "Model-based statistical sensor fusion for unexploded ordnance detection," in IEEE International Geoscience and Remote Sensing Symposium, IGARSS 2002, Toronto, Ontario, Canada, 24-28 June 2002, IEEE, 2002, pp. 1556–1559.	object detection, sensor fusion	test field	not specified	buried	other UXO	metal	metal detector, magnetometer, electro magnetic induction	naive bayes	ROC, detection rate, false alarm rate	"limiting the processing bandwidth to those frequencies that are the most robust to naturally occurring geological noise" optimizes sensor fusion
2001	L. M. Collins et al., "A comparison of the performance of statistical and fuzzy algorithms for unexploded ordnance detection," IEEE Trans. Fuzzy Syst., vol. 9, no. 1, pp. 17–30, 2001.	object detection, sensor fusion	test field	not specified		other UXO	metal	metal detector, magnetometer, electro magnetic induction	neural network, naive bayes, k-means	ROC, detection rate, false alarm rate	Bayesian approach is beneficial for sensor fusion and radar object detection
2012	M. Elkattan, A. Salem, F. Soliman, A. Kamel, and H. El-Hennawy, "Microcontroller Based Neural Network for Landmine Detection using Magnetic Gradient Data," in 2012 4TH INTERNATIONAL CONFERENCE ON INTELLIGENT AND ADVANCED SYSTEMS (ICIAS), VOLS 1-2, 345 E 47TH ST, NEW YORK, NY 10017 USA: IEEE, 2012, pp. 46–50.	object detection	test field	not specified	buried	AT landmine, landmine	metal	metal detector, gradiometer	neural network	error distance (cm)	Microcontroller-based NN can be used for real-time landmine detection from gradiometer data
1999	A. Filippidis, L. C. Jain, and P. Lozo, "Degree of familiarity ART2 in knowledge-based landmine detection," IEEE Trans. Neural Netw., vol. 10, no. 1, pp. 186–193, 1999.	object detection	test field	not specified		AP landmine, landmine	metal, minimal-metal, plastic	image data , thermal images, hyperspectral images	neural network	detection rate, false alarm rate	Fusion of multispectral and thermal imaging via NN outperforms single sensor detection
2005	H. Frigui, K. C. Ho, and P. D. Gader, "Real-Time Landmine Detection with Ground-Penetrating Radar Using Discriminative and Adaptive Hidden Markov Models," EURASIP J. Adv. Signal Process., vol. 2005, no. 12, pp. 1867–1885, 2005.	object detection	test field	vehicle mounted	different soil types, buried	AT landmine, landmine	metal, minimal-metal, plastic	ground penetrating radar	hidden markov model	ROC, detection rate, false alarm rate	Hidden Markov Models for GPR data improve detection performance by 10% on average

Year	Source	Study aim	Data acquisition	Acquisition device	Specific field conditions	ERW types	ERW material	Input features	AI algorithm	Result metrics	Key findings for literature review
2001	P. D. Gader, M. Mystkowski, and Y. Zhao, "Landmine detection with ground penetrating radar using hidden Markov models," IEEE Trans. Geosci. Remote Sens., vol. 39, no. 6, pp. 1231–1244, 2001.	object detection	test field	vehicle mounted	different soil types, buried	AT landmine, landmine	metal, minimal-metal, plastic	ground penetrating radar	hidden markov model	ROC, detection rate, false alarm rate	Hidden Markov Models for GPR can generalize landmine detection between different test sites
2000	P. Gao and L. M. Collins, "A two-dimensional generalized likelihood ratio test for land mine and small unexploded ordnance detection," Signal Processing, vol. 80, no. 8, pp. 1669–1686, 2000.	object detection	test field	not specified	different soil types, buried	AP landmine, landmine, other UXO	metal	metal detector, electro magnetic induction	likelihood ratio test	ROC, detection rate, false alarm rate	Generalized likelihood ratio test method can significantly reduce FAR in landmine detection
2015	F. Giovanneschi and M. A. Gonzalez-Huici, "A Preliminary analysis of a Sparse Reconstruction Based Classification method applied to GPR data," in 2015 8TH INTERNATIONAL WORKSHOP ON ADVANCED GROUND PENETRATING RADAR (IWAGPR), 345 E 47TH ST, NEW YORK, NY 10017 USA: IEEE, 2015.	object detection	test field	not specified	buried	AP landmine, AT landmine	metal, minimal-metal, plastic	ground penetrating radar	support vector machine, basis pursuit denoise, orthogonal matching pursuit	detection rate, false alarm rate	Sparse Reconstruction Based Classification method with basis pursuit denoising can detect and classify landmines from GPR
2019	F. Giovanneschi, K. V. Mishra, M. A. Gonzalez-Huici, Y. C. Eldar, and J. H. G. Ender, "Dictionary Learning for Adaptive GPR Landmine Classification," IEEE Trans. Geosci. Remote Sens., vol. 57, no. 12, pp. 10036–10055, Dec. 2019.	object detection	test field	not specified	buried	AP landmine, AT landmine	metal, minimal-metal, plastic	ground penetrating radar	support vector machine, neural network, convolutional neural network	detection rate, false alarm rate	"Online [Dictionary Learning] methods reduce learning time by 36-93% and increase mine detection by 4-28%" over a SVM-based approach
2021	S. Gutierrez et al., "Advances on the detection of Landmines and IEDs in Colombia using UWB GPR and Machine Learning Techniques," in 2021 15TH EUROPEAN CONFERENCE ON ANTENNAS AND PROPAGATION (EUCAP), in Proceedings of the European Conference on Antennas and Propagation. 345 E 47TH ST, NEW YORK, NY 10017 USA: IEEE, 2021.	object detection	test field	not specified	different soil types	improvised explosive device	not specified	ground penetrating radar	support vector machine	accuracy, specificity, recall	SVM trained with GPR data can outperform metal detector for identifying IED
2010	A. Hamdi, O. Missaoui, and H. Frigui, "AN SVM classifier with HMM-based kernel for landmine detection using ground penetrating radar," in IEEE International Symposium on Geoscience and Remote Sensing IGARSS. Jul. 2010, pp. 4196–4199.	object detection	test field	vehicle mounted		AT landmine, landmine		ground penetrating radar	support vector machine, hidden markov model	ROC, detection rate, false alarm rate	"[SVM with] HMM-based kernel [...] is less sensitive to the positioning error [of the landmine]"
2015	A. Hamdi and H. Frigui, "Ensemble hidden Markov models with application to landmine detection," EURASIP J. Adv. Signal Process., vol. 2015, p. 75, Aug. 2015.	object detection	test field	vehicle mounted	different soil types, buried	landmine	not specified	ground penetrating radar	neural network, ensemble methods, hidden markov model	AUC, ROC, detection rate, false alarm rate	Ensemble of HMM outperforms single HMM
2001	S. J. Hart, R. E. Shaffer, S. L. Rose-Pehrsson, and J. R. McDonald, "Using physics-based modeler outputs to train probabilistic neural networks for unexploded ordnance (UXO) classification in magnetometry surveys," IEEE Trans. Geosci. Remote Sens., vol. 39, no. 4, pp. 797–804, 2001.	object detection	test field	not specified	buried	other UXO	metal	metal detector, magnetometer	neural network	detection rate, false alarm rate	NN trained with magnetometer data is able to generalize across test sites for UXO detection
2002	K. C. Ho and P. D. Gader, "A linear prediction land mine detection algorithm for hand held ground penetrating radar," IEEE Trans. Geosci. Remote Sens., vol. 40, no. 6, pp. 1374–1384, Jun. 2002.	object detection	test field	handheld device	different soil types, buried	AP landmine, AT landmine	metal, plastic	ground penetrating radar	linear / logistic regression	ROC, detection rate, false alarm rate	Efficient, simple linear prediction methods achieve good results for landmine detection from GPR data
2009	W. Jian-bin, T. Mao, and L. Yu-tao, "Feature extraction and recognition of landmine," in Proceedings of the 5th International Conference on Wireless communications, networking and mobile computing, in WiCOM'09. IEEE Press, Sep. 2009, pp. 2135–2138.	object detection	test field	not specified	different soil types, buried	landmine	plastic	ground penetrating radar	support vector machine	detection rate	Feature extraction improves performance for SVM-based landmine detection from GPR data
2006	T. Jin, Z. Zhou, Q. Song, and W. Chang, "The evidence framework applied to fuzzy hypersphere SVM for UWB SAR landmine detection," in 2006 8th international Conference on Signal Processing, IEEE, 2006. doi: 10.1109/ICOSP.2006.345920.	object detection	test field	not specified	buried	AT landmine, landmine	metal	ground penetrating radar, ultra-wideband radar	support vector machine	false alarm rate	"The Fuzzy HyperSphere Support Vector Machine has stronger generalization capability than the HyperPlane SVM in UWB SAR landmine detection."

Year	Source	Study aim	Data acquisition	Acquisition device	Specific field conditions	ERW types	ERW material	Input features	AI algorithm	Result metrics	Key findings for literature review
2008	T. Jin and Z. Zhou, "Feature Extraction and Discriminator Design for Landmine Detection on Double-Hump Signature in Ultrawideband SAR," IEEE Trans. Geosci. Remote Sens., vol. 46, no. 11, 2, pp. 3783–3791, Nov. 2008.	object detection	test field	not specified	different soil types, buried	AT landmine, landmine	metal	ground penetrating radar, ultra-wideband radar	support vector machine, hidden markov model	ROC, detection rate, false alarm rate	SVM-based landmine detection from UWB data with HMM improves performance
2012	T. Jin, J. Lou, and Z. Zhou, "Extraction of Landmine Features Using a Forward-Looking Ground-Penetrating Radar With MIMO Array," IEEE Trans. Geosci. Remote Sens., vol. 50, no. 10, pp. 4135–4144, Oct. 2012.	object detection	test field	vehicle mounted	different soil types, buried	landmine	not specified	ground penetrating radar	space-wavenumber processing	ROC, detection rate, false alarm rate	Feature extraction improves performance for landmine detection from GPR data
2023	M. Bajic and B. Potoenic, "UAV Thermal Imaging for Unexploded Ordnance Detection by Using Deep Learning," Remote. Sens., vol. 15, no. 4, p. 967, 2023.	object detection	real-world	UAV / drone	different soil types	landmine	metal	image data, thermal images	neural network, convolutional neural network	detection rate, precision, recall	Pretrained CNNs can detect UXO from thermal UAV image data
2018	V. Kafedziski, S. Pecov, and D. Tanevski, "Detection and Classification of Land Mines from Ground Penetrating Radar Data Using Faster R-CNN," in 2018 26TH TELECOMMUNICATIONS FORUM (TELFOR), 345 E 47TH ST, NEW YORK, NY 10017 USA: IEEE, Nov. 2018, pp. 392–395.	object detection	test field	not specified	buried	AP landmine, AT landmine, landmine	not specified	ground penetrating radar	neural network, convolutional neural network	ROC, detection rate, false alarm rate, confusion matrix	Pretrained CNNs can detect landmines from GPR data
2011	A. Karem and H. Frigui, "A multiple instance learning approach for landmine detection using Ground Penetrating Radar," in 2011 IEEE International Geoscience and Remote Sensing Symposium, IGARSS 2011, Vancouver, BC, Canada, July 24–29, 2011, IEEE, 2011, pp. 878–881.	object detection	test field	vehicle mounted	different soil types, buried	AT landmine, landmine	metal, minimal-metal	ground penetrating radar	relevance vector machine, linear / logistic regression	ROC, detection rate, false alarm rate	Summarizing the training landmine alarms by few representatives improves learning
2018	P. Klesk, M. Kapruziak, and B. Olech, "Statistical moments calculated via integral images in application to landmine detection from Ground Penetrating Radar 3D scans," Pattern Anal. Appl., vol. 21, no. 3, pp. 671–684, Aug. 2018.	object detection	test field	not specified	buried	AT landmine, landmine	metal, plastic	ground penetrating radar	tree-based algorithm, RealBoost with decision trees, ensemble methods	ROC, detection rate, false alarm rate, sensitivity	Random Forest methods on GPR data outperform approach based on 3D statistical moments for landmine detection
2015	P. Klesk, M. Kapruziak, and B. Olech, "A Comparison of Shallow Decision Trees Under Real-Boost Procedure with Application to Landmine Detection Using Ground Penetrating Radar," in Artificial Intelligence and Soft Computing - 14th International Conference, ICAISC 2015, Zakopane, Poland, June 14–18, 2015, Proceedings, Part I, L. Rutkowski, M. Korytkowski, R. Scherer, R. Tadeusiewicz, L. A. Zadeh, and J. M. Zurada, Eds., in Lecture Notes in Computer Science, vol. 9119. Springer, 2015, pp. 436–447.	object detection	test field	not specified		AT landmine, landmine	metal, plastic	ground penetrating radar	tree-based algorithm, RealBoost with decision trees, ensemble methods	AUC, ROC, detection rate, false alarm rate, sensitivity	Ensemble Boosting with Trees works well for GPR data
2010	M. P. Kolba, P. A. Torrione, and L. M. Collins, "Fusion of ground-penetrating radar and electromagnetic induction sensors for landmine detection and discrimination," in DETECTION AND SENSING OF MINES, EXPLOSIVE OBJECTS, AND OBSCURED TARGETS XV, R. S. Harmon, K. H. Holloway, and J. T. Broach, Eds., in Proceedings of SPIE, vol. 7664. 2010. doi: 10.1117/12.851364.	object detection, sensor fusion	test field	not specified		AP landmine, AT landmine, landmine	not specified	ground penetrating radar, metal detector, electro magnetic induction	tree-based algorithm, random forest, ensemble methods	ROC, detection rate, false alarm rate	Fusion of GPR and EMI improves performance for landmine detection
2006	T. Koçak and M. Draper, "A Back-propagation Neural Network Landmine Detector Using the Delta-technique and S-statistic," Neural Process. Letters, vol. 23, no. 1, pp. 47–54, Feb. 2006.	object detection	test field	not specified		landmine	not specified	metal detector, electro magnetic induction	neural network, delta-technique	ROC, detection rate	NN outperforms simple delta technique for EMI sensor recognition and generalizes well even with little data
2017	S. Lameri, F. Lombardi, P. Bestagini, M. Lualdi, and S. Tubaro, "Landmine detection from GPR data using convolutional neural networks," in 25th European Signal Processing Conference, EUSIPCO 2017, Kos, Greece, August 28 - September 2, 2017, IEEE, Aug. 2017, pp. 508–512.	object detection	test field	not specified	buried	landmine	not specified	ground penetrating radar	neural network, convolutional neural network	AUC, ROC, detection rate, false alarm rate, accuracy	CNN for GPR require only little preprocessing for successful landmine detection

Year	Source	Study aim	Data acquisition	Acquisition device	Specific field conditions	ERW types	ERW material	Input features	AI algorithm	Result metrics	Key findings for literature review
2007	W.-H. Lee, P. D. Gader, and J. N. Wilson, "Optimizing the area under a receiver operating characteristic curve with application to land-mine detection," IEEE Trans. Geosci. Remote Sens., vol. 45, no. 2, pp. 389–397, Feb. 2007.	object detection	test field	not specified		AT landmine, landmine	metal, plastic	ground penetrating radar	neural network	AUC, ROC, detection rate, false alarm rate	AUC/ROC optimization techniques lead to better results for NN and GPR
2010	J. M. Leiva-Murillo, L. Gomez-Chova, and G. Camps-Valls, "Multitask SVM learning for Remote Sensing Data Classification," in IMAGE AND SIGNAL PROCESSING FOR REMOTE SENSING XVI, L. Bruzzone, Ed., in Proceedings of SPIE, vol. 7830. 1000 20TH ST, PO BOX 10, BELLINGHAM, WA 98227-0010 USA: SPIE-INT SOC OPTICAL ENGINEERING, 2010. doi: 10.1117/12.865045.	object detection	test field	UAV / drone	different soil types	landmine	not specified	image data , hyperspectral images	support vector machine	AUC, ROC, detection rate, false alarm rate	Multitask SVM learning performs well for landmine detection from remote sensing data
2009	X. Liao and L. Carin, "Migratory Logistic Regression for Learning Concept Drift Between Two Data Sets With Application to UXO Sensing," IEEE Trans. Geosci. Remote Sens., vol. 47, no. 5, pp. 1454–1466, 2009.	object detection	test field	not specified	different soil types	other UXO	metal	metal detector, magnetometer, electro magnetic induction	linear / logistic regression	AUC, ROC, detection rate, false alarm rate	The MigLogit classifier improves generalization between two different test sites for UXO
2005	G. Q. Liu, Y. J. Sun, and J. Li, "Automatic target recognition with Bayesian networks for wide-area airborne minefield detection," in Detection and Remediation Technologies for Mines and Minelike Targets X, Pts 1 and 2, R. S. Harmon, J. T. Broach, and J. H. Holloway, Eds., in PROCEEDINGS OF THE SOCIETY OF PHOTO-OPTICAL INSTRUMENTATION ENGINEERS (SPIE), vol. 5794. 2005, pp. 1060–1070.	object detection, sensor fusion	test field	UAV / drone, airplane	different soil types, buried	landmine	metal, plastic	ground penetrating radar	bayesian network	ROC, detection rate, false alarm rate	Bayesian Networks enable sensor fusion and improve detection results
2008	Q. Liu, X. Liao, and L. Carin, "Detection of Unexploded Ordnance via Efficient Semisupervised and Active Learning," IEEE Trans. Geosci. Remote Sens., vol. 46, no. 9, pp. 2558–2567, 2008.	object detection	test field	not specified		other UXO	metal	metal detector, magnetometer, electro magnetic induction	nearest neighbors	ROC, detection rate, false alarm rate	Semi Supervised learning helps to keep contextual information in mine detection
2005	S. Merler, C. Furlanello, and G. Jurman, "Machine Learning on Historic Air Photographs for Mapping Risk of Unexploded Bombs," in Image Analysis and Processing - ICIAP 2005, 13th International Conference, Cagliari, Italy, September 6-8, 2005, Proceedings, F. Roli and S. Vitulano, Eds., in Lecture Notes in Computer Science, vol. 3617. Springer, 2005, pp. 735–742.	risk prediction	real-world	airplane		other UXO	metal	image data , hyperspectral images	tree-based algorithm, other-tree based algorithm, ensemble methods, nearest neighbors	false alarm rate, accuracy, sensitivity, specificity	Simple, historic images with tree based ensemble methods can be used to predict a probability of UXO.
2011	O. Missaoui, H. Frigui, and P. Gader, "Land-Mine Detection With Ground-Penetrating Radar Using Multistream Discrete Hidden Markov Models," IEEE Trans. Geosci. Remote Sens., vol. 49, no. 6, 1, pp. 2080–2099, Jun. 2011.	object detection	test field	vehicle mounted	different soil types, buried	AP landmine, AT landmine, landmine	metal, minimal-metal	ground penetrating radar	hidden markov model	ROC, detection rate, false alarm rate	Multistream HMM outperform single stream HMM for landmine detection from GPR data
2004	N. Mudigonda, R. Kacelenga, and M. Edwards, "Holographic neural networks versus conventional neural networks: A comparative evaluation for the classification of landmine targets in ground penetrating radar images," in PROCEEDINGS OF THE SOCIETY OF PHOTO-OPTICAL INSTRUMENTATION ENGINEERS (SPIE), vol. 5415. 2004, pp. 996–1007.	object detection	test field	vehicle mounted		landmine	not specified	ground penetrating radar	neural network, convolutional neural network	AUC, ROC, detection rate, false alarm rate	Holographic NN outperforms standard NN in terms of generalization across sites
2014	X. Núñez-Nieto, M. Solla, P. Gómez-Pérez, and H. Lorenzo, "GPR Signal Characterization for Automated Landmine and UXO Detection Based on Machine Learning Techniques," Remote. Sens., vol. 6, no. 10, pp. 9729–9748, 2014.	object detection	test field	not specified	buried	AP landmine, AT landmine, landmine, other UXO	plastic	ground penetrating radar	linear / logistic regression, neural network	false alarm rate, accuracy	NN outperforms logistic regression for landmine detection from GPR

Year	Source	Study aim	Data acquisition	Acquisition device	Specific field conditions	ERW types	ERW material	Input features	AI algorithm	Result metrics	Key findings for literature review
2018	F. Picetti, G. Testa, F. Lombardi, P. Bestagini, M. Lualdi, and S. Tubaro, "Convolutional Autoencoder for Landmine Detection on GPR Scans," in 41st International Conference on Telecommunications and Signal Processing, TSP 2018, Athens, Greece, July 4-6, 2018, IEEE, 2018, pp. 1-4.	object detection	test field	not specified	buried	landmine	not specified	ground penetrating radar	neural network, convolutional neural network, autoencoder	AUC, ROC, detection rate, false alarm rate	Autoencoders can easily be trained on each new site
1997	G. L. Plett, T. Doi, and D. Torrieri, "Mine detection using scattering parameters and an artificial neural network," IEEE Trans. Neural Netw., vol. 8, no. 6, pp. 1456-1467, Nov. 1997.	object detection	test field	not specified		AP landmine, landmine	metal, plastic	microwave sensor	neural network, nearest neighbors	detection rate, false alarm rate	Neural networks for landmine detection from microwave data benefits from preprocessing like outlier removal
2021	M. O. Popov, S. A. Stankevich, S. P. Mosov, O. V. Titarenko, M. V. Topolnytskyi, and S. S. Dugin, "Landmine Detection with UAV-based Optical Data Fusion," in 19th IEEE International Conference on Smart Technologies, EUROCON 2021, Lviv, Ukraine, July 6-8, 2021, IEEE, Jul. 2021, pp. 175-178.	object detection, sensor fusion	test field	UAV / drone	buried	landmine	not specified	image data , thermal images, hyperspectral images	linear / logistic regression, ensemble methods	detection rate, false alarm rate	Sensor fusion with multiple linear and statistical models is capable of landmine identification from UAV multispectral image data
2006	D. Potin, P. Vanheghe, E. Duflos, and M. Davy, "An abrupt change detection algorithm for buried landmines localization," IEEE Trans. Geosci. Remote Sens., vol. 44, no. 2, pp. 260-272, Feb. 2006.	object detection	test field	#VALUE!	buried	AP landmine, landmine	metal	ground penetrating radar	support vector machine	ROC, detection rate, false alarm rate	SVM is capable of abrupt change detection for AP landmine detection from GPR
2015	J. Prado, S. Filipe, and L. Marques, "Bayesian sensor fusion for multi-platform landmines detection," in 2015 European Conference on Mobile Robots (ECMR), IEEE, Sep. 2015, pp. 1-6.	object detection, sensor fusion	test field	not specified		AP landmine, AT landmine, landmine	metal, minimal-metal	ground penetrating radar, metal detector	bayesian network	detection rate, false alarm rate	Bayesian Networks enable sensor fusion and improve detection results
2017	J. Prado and L. Marques, "Reducing false-positives in multi-sensor dataset of landmines via sensor fusion regularization," in 2017 IEEE International Conference on Autonomous Robot Systems and Competitions, ICARSC 2017, Coimbra, Portugal, April 26-28, 2017, L. Marques and A. Bernardino, Eds., IEEE, Apr. 2017, pp. 204-209.	object detection, sensor fusion	test field	not specified	different soil types, buried	landmine	metal, minimal-metal	ground penetrating radar, metal detector	linear / logistic regression	ROC, detection rate, false alarm rate, precision, accuracy, recall	Regularized sensor fusion improves performance for landmine detection
2021	C. N. N. Priya, S. D. Ashok, B. Majhi, and K. S. Kumaran, "Deep Learning Based Thermal Image Processing Approach for Detection of Buried Objects and Mines," ENGINEERING JOURNAL-THAILAND, vol. 25, no. 3, pp. 61-67, 2021.	object detection	test field	vehicle mounted	buried		metal, plastic	image data , thermal images	neural network, convolutional neural network	accuracy	CNN achieves high accuracy in identifying buried landmines from thermal images
2023	Z. Qiu, H. Guo, J. Hu, H. Jiang, and C. Luo, "Joint Fusion and Detection via Deep Learning in UAV-Borne Multispectral Sensing of Scatterable Landmine," Sensors, vol. 23, no. 12, p. 5693, Jun. 2023.	object detection, sensor fusion	test field	UAV / drone		AP landmine, AT landmine, landmine	metal	image data , thermal images, hyperspectral images	neural network	detection rate, false alarm rate, precision, recall	Fusion of thermal and RGB image data can achieve worse results than only RGB.
2019	W. Raffique, D. Zheng, J. Barras, S. Joglekar, and P. Kosmas, "Predictive Analysis of Landmine Risk," IEEE ACCESS, vol. 7, pp. 107259-107269, 2019.	risk prediction	real-world	not specified	different soil types, buried	landmine	not specified	ERW records, infrastructure data, topology data	support vector machine, linear / logistic regression, ensemble methods	AUC, ROC, detection rate, false alarm rate	Simple ML models like SVM or logistic regression can perform probability density prediction of landmines over large areas from topological and infrastructure data
2011	C. R. Ratto, K. D. Morton Jr, L. M. Collins, and P. A. Torrione, "Contextual Learning in Ground-Penetrating Radar Data Using Dirichlet Process Priors," in DETECTION AND SENSING OF MINES, EXPLOSIVE OBJECTS, AND OBSCURED TARGETS XVI, R. S. Harmon, J. H. Holloway, and J. T. Broach, Eds., in Proceedings of SPIE, vol. 8017. 2011. doi: 10.1117/12.884872.	object detection	test field	vehicle mounted	different soil types, buried	AT landmine, landmine	metal, minimal-metal	ground penetrating radar	relevance vector machine, ensemble methods, principal component analysis, gaussian mixture model	ROC, detection rate, false alarm rate	Context-dependent model fusion improves landmine detection performance for GPR data
2011	C. R. Ratto, P. A. Torrione, and L. M. Collins, "Exploiting Ground-Penetrating Radar Phenomenology in a Context-Dependent Framework for Landmine Detection and Discrimination," IEEE Trans. Geosci. Remote Sens., vol. 49, no. 5, pp. 1689-1700, May 2011.	object detection	test field	vehicle mounted	different soil types, buried	AT landmine, landmine	metal, minimal-metal	ground penetrating radar	relevance vector machine, ensemble methods	ROC, detection rate, false alarm rate, confusion matrix	Context-dependent model fusion especially improves reduction of false alarm rates for landmine detection

Year	Source	Study aim	Data acquisition	Acquisition device	Specific field conditions	ERW types	ERW material	Input features	AI algorithm	Result metrics	Key findings for literature review
2011	C. R. Ratto, K. Morton, L. M. Collins, and P. Torrione, "A hidden Markov context model for GPR-based landmine detection incorporating stick-breaking priors," in 2011 IEEE International Geoscience and Remote Sensing Symposium, IGARSS 2011, Vancouver, BC, Canada, July 24-29, 2011, IEEE, 2011, pp. 874-877.	object detection	test field	vehicle mounted	different soil types, buried	AT landmine, landmine	metal, minimal-metal	ground penetrating radar	relevance vector machine, ensemble methods, hidden markov model	ROC, detection rate, false alarm rate	Context-dependent model fusion improves landmine detection performance for GPR data
2017	D. Reichman, L. M. Collins, and J. M. Malof, "The effect of translational variance in training and testing images on supervised buried threat detection algorithms for ground penetrating radar," in 2017 9th International Workshop on Advanced Ground Penetrating Radar (IWAGPR), IEEE, Jun. 2017, pp. 1-6.	object detection	test field	vehicle mounted		landmine	not specified	ground penetrating radar	tree-based algorithm, random forest, ensemble methods	AUC, ROC, detection rate, false alarm rate	Mitigating translational variance in GPR scans improves detection performance
2006	S. R. Riese, D. E. Brown, and Y. Y. Haimes, "Estimating the probability of landmine contamination," MILITARY OPERATIONS RESEARCH, vol. 11, no. 3, pp. 49-61, 2006.	risk prediction	real-world	not specified		landmine	not specified	ERW incident data, ERW records, infrastructure data, topology data	naive bayes	confusion matrix	Simple bayesian approach with Meta-Gaussian model performs accurate predictions of landmine probability in a given area for real world data
2023	M. D. Rubio et al., "RELand: Risk Estimation of Landmines via Interpretable Invariant Risk Minimization," CoRR, vol. abs/2311.03115, 2023, doi: 10.48550/ARXIV.2311.03115.	risk prediction	real-world	not specified		landmine	not specified	ERW incident data, ERW records, infrastructure data, topology data	neural network	AUC, ROC, detection rate, false alarm rate	TabNet (attention tech) enables prediction of landmine risks for large regions across countries
2024	A. Saliba, K. Tout, C. Zaki, and C. Claramunt, "A location-based model using GIS with machine learning, and a human-based approach for demining a post-war region," JOURNAL OF LOCATION BASED SERVICES, 2024, doi: 10.1080/17489725.2023.2298803.	risk prediction	real-world	not specified		landmine	not specified	ERW records, infrastructure data, topology data	support vector machine, tree-based algorithm, random forest, other-tree based algorithm, ensemble methods	AUC, ROC, detection rate, false alarm rate, precision, accuracy, recall	Including prior military knowledge (e.g., conflict lines) improves landmine risk prediction
2018	X. Shi, D. Cheng, Z. Song, and C. Wang, "A Real-time Method For Landmine Detection Using Vehicle Array GPR," in 2018 17th International Conference on Ground Penetrating Radar (GPR), IEEE, Jun. 2018, pp. 1-4.	object detection	test field	vehicle mounted	buried	AT landmine, landmine	metal, plastic	ground penetrating radar	support vector machine	detection rate, false alarm rate	Landmine detection from GPR data is feasible in real time
2011	Y. Shi, Q. Song, T. Jin, and Z. Zhou, "Landmine detection using boosting classifiers with adaptive feature selection," in 2011 6th International Workshop on Advanced Ground Penetrating Radar (IWAGPR), IEEE, Jun. 2011, pp. 1-5.	object detection	test field	vehicle mounted	buried	AT landmine, landmine	not specified	ground penetrating radar	support vector machine, ensemble methods	ROC, detection rate, false alarm rate	Ensemble Boosting with SVMs works well for GPR data
2019	J. S. Silva, I. F. Linhas Guerra, J. Bioucas-Dias, and T. Gasche, "Landmine Detection Using Multispectral Images," IEEE Sens. J., vol. 19, no. 20, SI, pp. 9341-9351, Oct. 2019.	object detection	test field	not specified	different soil types, buried	AP landmine, AT landmine, landmine	not specified	image data , thermal images, hyperspectral images	support vector machine, neural network, convolutional neural network, tree-based algorithm, other-tree based algorithm, ensemble methods, nearest neighbors	accuracy	SVM outperforms CNN in landmine detection from multispectral images
2007	R. J. Stanley, K. C. Ho, P. Gader, J. N. Wilson, and J. Devaney, "Land Mine and Clutter Object Discrimination Using Wavelet and Time Domain Spatially Distributed Features from Metal Detectors and Their Fusion with GPR Features for Hand-Held Units," Circuits Systems Signal Process., vol. 26, no. 2, pp. 165-191, Apr. 2007.	object detection, sensor fusion	test field	handheld device	buried	AP landmine, AT landmine, landmine	metal, minimal-metal	ground penetrating radar, metal detector	neural network	ROC, detection rate, false alarm rate	Fusion of metal detector and GPR data is supported by preprocessing of the data
2002	R. J. Stanley, P. D. Gader, and K. C. Ho, "Feature and decision level sensor fusion of electromagnetic induction and ground penetrating radar sensors for landmine detection with hand-held units," Inf. Fusion, vol. 3, no. 3, pp. 215-223, 2002.	object detection, sensor fusion	test field	handheld device	different soil types, buried	AP landmine, AT landmine, landmine	metal, minimal-metal	ground penetrating radar, metal detector, electro magnetic induction	neural network	ROC, detection rate, false alarm rate	Feature level fusion outperforms decision level fusion and the GPR and MD in isolation consistently

Year	Source	Study aim	Data acquisition	Acquisition device	Specific field conditions	ERW types	ERW material	Input features	AI algorithm	Result metrics	Key findings for literature review
2001	R. J. Stanley, N. Theera-Umpon, P. Gader, S. Somanchi, and D. Ho, "Detecting landmines using weighted density distribution function features," in SIGNAL PROCESSING, SENSOR FUSION, AND TARGET RECOGNITION X, I. Kadar, Ed., in PROCEEDINGS OF THE SOCIETY OF PHOTO-OPTICAL INSTRUMENTATION ENGINEERS (SPIE), vol. 4380. 2001, pp. 135–141.	object detection	test field	handheld device	different soil types, buried	AP landmine, AT landmine, landmine	metal, minimal-metal	metal detector	neural network	ROC, detection rate, false alarm rate	Spatially distributed features based on correlating sequences of metal detector energy values with weighted density distribution functions improve landmine detection performance.
2018	K. Tbarki, S. Ben Said, R. Ksantini, and Z. Lachiri, "Adaptive landmine detection and localization system based on incremental one-class classification," J. Appl. Remote Sens., vol. 12, no. 3, Jul. 2018, doi: 10.1117/1.JRS.12.036002.	object detection	test field	not specified	different soil types, buried	AP landmine, landmine	metal, minimal-metal, plastic	ground penetrating radar	support vector machine	AUC, ROC, detection rate, false alarm rate	Incremental covariance-guided one-class SVM improve landmine detection from GPR
2018	K. Tbarki, S. Ben Said, R. Ksantini, and Z. Lachiri, "Covariance-guided landmine detection and discrimination using ground-penetrating radar data," Int. J. Remote Sens., vol. 39, no. 2, pp. 289–314, Jan. 2018.	object detection	test field	not specified	different soil types, buried	AP landmine, landmine	metal, minimal-metal, plastic	ground penetrating radar	support vector machine	AUC, ROC, detection rate, false alarm rate	Covariance-guided one-class SVM improve landmine detection from GPR
2016	K. Tbarki, S. B. Said, R. Ksantini, and Z. Lachiri, "RBF kernel based SVM classification for landmine detection and discrimination," in International Image Processing, Applications and Systems, IPAS 2016, Hammamet, Tunisia, November 5-7, 2016, IEEE, 2016, pp. 1–6.	object detection	test field	not specified	different soil types, buried	AP landmine, landmine	metal, minimal-metal, plastic	ground penetrating radar	support vector machine	AUC, ROC, detection rate, false alarm rate	SVM with RBF Kernel performs well for landmine detection from GPR data
2017	K. Tbarki, S. B. Said, R. Ksantini, and Z. Lachiri, "Landmine detection improvement using one-class SVM for unbalanced data," in 2017 International Conference on Advanced Technologies for Signal and Image Processing (ATSIP), Fez, Morocco, May 22-24, 2017, M. E. Hassouni, M. Karim, A. B. Hamida, A. B. Slima, and B. Solaiman, Eds., IEEE, May 2017, pp. 1–6.	object detection	test field	not specified	different soil types, buried	AP landmine, landmine	metal, minimal-metal, plastic	ground penetrating radar	support vector machine	AUC, ROC, detection rate, false alarm rate	One class SVM with RBF outperforms multi class SVM with other kernels for landmine detection from GPR data
2004	N. Theera-Umpon and S. Auephanwiriyakul, "Unexploded ordnance detection by measuring object symmetry via linear prediction," in 2004 IEEE Region 10 Conference TENCN 2004., IEEE, 2004, pp. 195–198 Vol. 1.	object detection	test field	not specified	buried	other UXO	metal	ground penetrating radar	linear / logistic regression	ROC, detection rate, false alarm rate	Predicting the symmetry of an object improves UXO detection rates from GPR data
2010	A. M. Thomas and J. M. Cathcart, "Applications of Grid Pattern Matching to the Detection of Buried Landmines," IEEE Trans. Geosci. Remote Sens., vol. 48, no. 9, pp. 3465–3470, Sep. 2010.	object detection	test field	helicopter	buried	AP landmine, AT landmine, landmine	not specified	image data , thermal images, hyperspectral images	likelihood ratio test, dual window-based eigen separation transform (DWEST)	ROC, detection rate, false alarm rate	Spatial pattern information improves the detection of landmines in minefields from multispectral image data
2006	J. Tian, Z. Zhi-min, C. Wen-ge, and S. Qian, "Aspect-invariant feature extraction and associated landmine detector in UWBSAR," in PROCEEDINGS OF 2006 CIE INTERNATIONAL CONFERENCE ON RADAR, VOLS 1 AND 2, S. J. Wu, Ed., 345 E 47TH ST, NEW YORK, NY 10017 USA: IEEE, 2006, p. 607+.	object detection	test field	not specified	different soil types, buried	landmine	not specified	ground penetrating radar, ultra-wideband radar	support vector machine	ROC, detection rate, false alarm rate	Hypersphere SVM outperforms hyperplane SVM in landmine detection from UWB data
2022	F. H. C. Tivive, A. Bouzardoum, and C. Abeynayake, "Classification of Improvised Explosive Devices Using Multilevel Projective Dictionary Learning With Low-Rank Prior," IEEE Trans. Geosci. Remote Sens., vol. 60, pp. 1–16, 2022.	object detection	test field	vehicle mounted	buried	improvised explosive device	metal, minimal-metal	ground penetrating radar	support vector machine, neural network, convolutional neural network	confusion matrix, accuracy	Dictionary learning method outperforms ML techniques (SVM, MLP, CNN) for IED detection from GPR data.
2011	P. Torrione, K. Morton Jr, and L. E. Besaw, "Adaptive Gaussian Mixture Models for Pre-Screening in GPR Data," in DETECTION AND SENSING OF MINES, EXPLOSIVE OBJECTS, AND OBSCURED TARGETS XVI, R. S. Harmon, J. H. Holloway, and J. T. Broach, Eds., in Proceedings of SPIE, vol. 8017. 2011. doi: 10.1117/12.884136.	object detection	test field	vehicle mounted	different soil types, buried	AT landmine, landmine	metal, plastic	ground penetrating radar	gaussian mixture model	ROC, detection rate, false alarm rate	GPR pre-processing using GMM outperforms the simpler squared energy based metric

Year	Source	Study aim	Data acquisition	Acquisition device	Specific field conditions	ERW types	ERW material	Input features	AI algorithm	Result metrics	Key findings for literature review
2011	P. Torrione, K. Morton Jr, and L. E. Besaw, "Sensor Fusion Approaches for EMI & GPR Based Subsurface Threat Identification," in DETECTION AND SENSING OF MINES, EXPLOSIVE OBJECTS, AND OBSCURED TARGETS XVI, R. S. Harmon, J. H. Holloway, and J. T. Broach, Eds., in Proceedings of SPIE, vol. 8017. 2011. doi: 10.1117/12.884130.	object detection, sensor fusion	test field	vehicle mounted	different soil types, buried	AT landmine, landmine	metal, plastic	ground penetrating radar, metal detector, electro magnetic induction	support vector machine, tree-based algorithm, random forest, ensemble methods, naive bayes, likelihood ratio test	ROC, detection rate, false alarm rate	Simple logistic discriminant classification is sufficient for fusion across sensors
2006	P. Torrione, J. Remus, and L. Collins, "Comparison of pattern recognition approaches for multi-sensor detection and discrimination of anti-personnel and anti-tank landmines," in DETECTION AND REMEDIATION TECHNOLOGIES FOR MINES AND MINELIKE TARGETS XI, PTS 1 AND 2, J. T. Broach, R. S. Harmon, and J. H. Holloway, Eds., in Proceedings of SPIE, vol. 6217. 2006. doi: 10.1117/12.665660.	object detection, sensor fusion	test field	vehicle mounted		AP landmine, AT landmine, landmine	metal, minimal-metal	ground penetrating radar, metal detector, electro magnetic induction	relevance vector machine	ROC, detection rate, false alarm rate	Fusion via RVM with a combination of linear and RBF kernels provides most robust results for landmine detection from GPR and EMI data
2012	M. D.-J. Tran, C. Abeynayake, and L. C. Jain, "A Target Discrimination Methodology Utilizing Wavelet-Based and Morphological Feature Extraction With Metal Detector Array Data," IEEE Trans. Geosci. Remote Sens., vol. 50, no. 1, pp. 119–129, Jan. 2012.	object detection	test field	vehicle mounted	buried	AP landmine, AT landmine, landmine	metal	metal detector	neural network	ROC, detection rate, false alarm rate, accuracy	Feature extraction and decision fusion improve landmine detection performance from metal detector data
2019	W. van Verre, T. Ozdeger, A. Gupta, F. J. W. Podd, and A. J. Peyton, "Threat Identification in Humanitarian Demining Using Machine Learning and Spectroscopic Metal Detection," in Intelligent Data Engineering and Automated Learning - IDEAL 2019 - 20th International Conference, Manchester, UK, November 14-16, 2019, Proceedings, Part 1, H. Yin, D. Camacho, P. Tiño, A. J. Tallón-Ballesteros, R. Menezes, and R. Allmendinger, Eds., in Lecture Notes in Computer Science, vol. 11871. 2019, pp. 542–549.	object detection	test field	handheld device	buried	AP landmine, landmine	metal, minimal-metal	metal detector, magnetic induction spectroscopy	support vector machine, neural network	ROC, detection rate, false alarm rate, confusion matrix	NN outperforms SVM in landmine detection from Magnetic induction spectroscopy data
2014	P. A. van Vuuren, "LANDMINE DETECTION BY MEANS OF GROUND PENETRATING RADAR: A MODEL-BASED APPROACH," SAIEE AFRICA RESEARCH JOURNAL, vol. 105, no. 3, pp. 90–103, Sep. 2014.	object detection	test field	not specified	buried	AP landmine, AT landmine, landmine	metal, minimal-metal	ground penetrating radar	neural network, principal component analysis		NN does not perform well in detection of low-metal landmines from GPR data
2024	E. Vivoli, M. Bertini, and L. Capineri, "Deep Learning-Based Real-Time Detection of Surface Landmines Using Optical Imaging," Remote Sensing, vol. 16, no. 4, p. 677, Feb. 2024.	object detection	test field	vehicle mounted	different soil types	AP landmine, landmine	minimal-metal	image data , hyperspectral images	neural network, convolutional neural network	precision, F1 score, recall	Pre Trained CNNs can detect AP mines from RGB image data
2011	M.-H. Wei, W. R. Scott Jr, and J. H. McClellan, "LANDMINE DETECTION USING THE DISCRETE SPECTRUM OF RELAXATION FREQUENCIES," in 2011 IEEE INTERNATIONAL GEOSCIENCE AND REMOTE SENSING SYMPOSIUM (IGARSS), in IEEE International Symposium on Geoscience and Remote Sensing IGARSS. 345 E 47TH ST, NEW YORK, NY 10017 USA: IEEE, Jul. 2011, pp. 834–837.	object detection	test field	not specified		landmine	not specified	metal detector, electro magnetic induction	support vector machine, nearest neighbors	ROC, detection rate, false alarm rate	KNN offers robust performance for landmine detection but is computational less efficient than a SVM and hence not suitable for real-world application.
2007	D. P. Williams, "Gaussian process classification using image deformation," in 2007 IEEE INTERNATIONAL CONFERENCE ON ACOUSTICS, SPEECH, AND SIGNAL PROCESSING, VOL II, PTS 1-3, in International Conference on Acoustics Speech and Signal Processing ICASSP. 345 E 47TH ST, NEW YORK, NY 10017 USA: IEEE, 2007, pp. 605–608.	object detection	test field	not specified		landmine	not specified	image data , hyperspectral images	gaussian processes	ROC, detection rate, false alarm rate	Suggest that nonparametric Gaussian Process classifiers generalize better to new environments
2009	D. P. Williams, V. Myers, and M. S. Silvious, "Mine Classification With Imbalanced Data," IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, vol. 6, no. 3, pp. 528–532, Jul. 2009.	object detection	test field	not specified	buried	landmine	not specified	ground penetrating radar	linear / logistic regression	AUC, ROC, detection rate, false alarm rate	Infinitely imbalanced logistic regression outperforms standard logistic regression for landmine detection from GPR data

Year	Source	Study aim	Data acquisition	Acquisition device	Specific field conditions	ERW types	ERW material	Input features	AI algorithm	Result metrics	Key findings for literature review
2006	Y. Yan-Guang, S. Qian, and Z. Zhi-Min, "A novel method of landmines detection based on improved SVM," in 2006 8TH INTERNATIONAL CONFERENCE ON SIGNAL PROCESSING, VOLS 1-4, B. Z. Yuan, Q. Q. Ruan, and X. F. Tang, Eds., in International Conference on Signal Processing. 2006, p. 1827+.	object detection	test field	not specified	different soil types, buried	AT landmine, landmine	metal	ground penetrating radar	support vector machine, principal component analysis	detection rate, false alarm rate	PCA preprocessing improves performance of landmine detection with SVM from GPR data
2008	S. E. Yüksel, G. Ramachandran, P. Gader, J. Wilson, G. Heo, and D. Ho, "Hierarchical Methods for Landmine Detection with Wideband Electro-Magnetic Induction and Ground Penetrating Radar Multi-Sensor Systems," in IGARSS 2008 - 2008 IEEE International Geoscience and Remote Sensing Symposium, IEEE, Jul. 2008, pp. II-177-II-180.	object detection, sensor fusion	test field	not specified	different soil types, buried	AP landmine, AT landmine, landmine	metal, minimal-metal	ground penetrating radar, metal detector, electro magnetic induction	linear / logistic regression, ensemble methods, nearest neighbors	ROC, detection rate, false alarm rate	Hierarchical Mixture of Experts model results in high detection performance from GPR and EMI fusion
2012	S. E. Yüksel, J. Bolton, and P. D. Gader, "Landmine detection with Multiple Instance Hidden Markov Models," in IEEE International Workshop on Machine Learning for Signal Processing, MLSP 2012, Santander, Spain, September 23-26, 2012, IEEE, 2012, pp. 1-6.	object detection	test field	not specified	buried	landmine	not specified	ground penetrating radar	hidden markov model	ROC, detection rate, false alarm rate	Multiple Instance Hidden Markov Model outperforms standard Hidden Markov Model in landmine detection from GPR data
2016	S. E. Yüksel and P. D. Gader, "Context-based classification via mixture of hidden Markov model experts with applications in landmine detection," IET Comput. Vision, vol. 10, no. 8, pp. 873-883, Jul. 2016.	object detection	test field	not specified	buried	AP landmine, AT landmine, landmine	metal, minimal-metal	metal detector, electro magnetic induction	ensemble methods, hidden markov model	accuracy	Mixture of hidden Markov model experts improves landmine detection performance from EMI data
2008	B. Zhang, "Classification, identification, and modeling of unexploded ordnance in realistic environments," Massachusetts Institute of Technology, Cambridge, MA, USA, 2008. [Online]. Available: https://hdl.handle.net/1721.1/44722	object detection	test field	not specified	buried	other UXO	metal	metal detector, electro magnetic induction	support vector machine, neural network	confusion matrix, accuracy	Noise and clutter create difficulties for UXO detection from EMI data
2014	X. Zhang, J. Bolton, and P. D. Gader, "A New Learning Method for Continuous Hidden Markov Models for Subsurface Landmine Detection in Ground Penetrating Radar," IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens., vol. 7, no. 3, pp. 813-819, 2014.	object detection	test field	vehicle mounted	buried	landmine	not specified	ground penetrating radar	hidden markov model, gaussian mixture model	false alarm rate	Gibbs sampling to learn the parameters of Hidden Markov Models with Gaussian mixtures outperforms standard expectation-maximization and minimum classification error algorithms
2020	Y. Zhang, D. Orfeo, D. Huston, and T. Xia, "Software Defined Doppler Radar for Landmine Detection using GA-Optimized Machine Learning," in 2020 IEEE INTERNATIONAL RADAR CONFERENCE (RADAR), 345 E 47TH ST, NEW YORK, NY 10017 USA: IEEE, Apr. 2020, pp. 208-213.	object detection	test field	not specified	different soil types, buried	landmine	plastic	ground penetrating radar, doppler radar	support vector machine, linear / logistic regression, tree-based algorithm, random forest, ensemble methods	precision, accuracy, recall	Random Forest outperforms SVM and logistic regression for landmine detection from Doppler radar data
2023	Y. Zhang, Y. Song, and T. Jin, "Lightweight CFARnets for Landmine Detection in Ultrawideband SAR," Remote. Sens., vol. 15, no. 18, p. 4411, 2023.	object detection	test field	airplane	different soil types	landmine	not specified	ground penetrating radar, ultra-wideband radar	neural network	false alarm rate, precision, F1 score, recall	Constant false alarm rates detector NN achieves similar results to CNN while being more computationally efficient
2003	Y. Zhao, P. D. Gader, P. Chen, and Y. Zhang, "Training DHMMs of mine and clutter to minimize landmine detection errors," IEEE Trans. Geosci. Remote Sens., vol. 41, no. 5, 1, pp. 1016-1024, May 2003.	object detection	test field	vehicle mounted	different soil types, buried	AT landmine, landmine	metal, minimal-metal, plastic	ground penetrating radar	hidden markov model	ROC, detection rate, false alarm rate	Training Hidden Markov Models with evolutionary algorithms and generalized probabilistic reduces false alarm rates by a factor of two

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