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AI for ERW Detection in Clearance Operations - The State of Research

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Abstract

The clearance of explosive remnants of war (ERW) continues to be a predominantly manual and high-risk process that can benefit from advances in technology to improve its efficiency and effectiveness. In particular, research on artificial intelligence for ERW clearance has grown significantly in recent years. However, this research spans a wide range of fields, making it difficult to gain a comprehensive understanding of current trends and developments. Therefore, this article provides a literature review of academic research on AI for ERW detection for clearance operations. It finds that research can be grouped into two main streams, AI for ERW object detection and AI for ERW risk prediction, with the latter being much less studied than the former.

From the analysis of the eligible literature, we develop three opportunities for future research, including a call for renewed efforts in the use of AI for ERW risk prediction, the combination of different AI systems and data sources, and novel approaches to improve ERW risk prediction performance, such as pattern-based prediction.

Finally, we provide a perspective on the future of AI for ERW clearance. We emphasize the role of traditional machine learning for this task, the need to dynamically incorporate expert knowledge into the models, and the importance of effectively integrating AI systems with real-world operations.

The Need for an Overview of Research in AI for ERW Clearance

The survey and removal of explosive remnants of war (ERW) remains a predominantly manual and risky process with increasingly limited financial resources. Technology has the potential to significantly improve this process. Thus, several public and non-public organizations actively seek innovative research in technology to improve clearance efficiency and effectiveness [1], [2], [3], [4]. For example, the Oslo Action Plan, a political commitment signed by States Parties implementing obligations of the Anti-Personnel Mine Ban Convention, explicitly states in action 27 to "[t]ake appropriate steps to improve the effectiveness and efficiency of survey and clearance, including by promoting the research, application and sharing of innovative technological means to this effect" [5].

Research on artificial intelligence (AI) for mine action has seen a significant surge in recent years. At the Innovation Conference 2023, organized by the Geneva International Centre for Humanitarian Demining (GICHD), AI and data analysis featured prominently, being the focus of five out of eleven breakout sessions [8]. However, this research spans a diverse range of fields, including electrical engineering, statistics, and more, making it challenging to gain a comprehensive understanding of current trends and developments. Nevertheless, such an overview is essential for both researchers and practitioners in mine action, as it helps identify promising research areas, ensures the efficient allocation of resources, and facilitates real-world impact.

To address this, we conducted a comprehensive review of research publications on AI systems for ERW localization to support clearance operations. This review examines 100 eligible publications on AI systems for ERW clearance, published between 1997 and 2024 (see Figure 1). Specifically, it explores the types of data and AI models utilized in the research to identify gaps and suggest directions for future work. Our literature review followed a multi-step process with several screening stages to identify relevant studies. An initial keyword search across seven databases yielded 1,558 results. These publications were then thoroughly screened based on predefined inclusion criteria. Only empirical, peer-reviewed studies using real-world data (excluding computer simulations) and applying machine learning algorithms for ERW prediction were included.

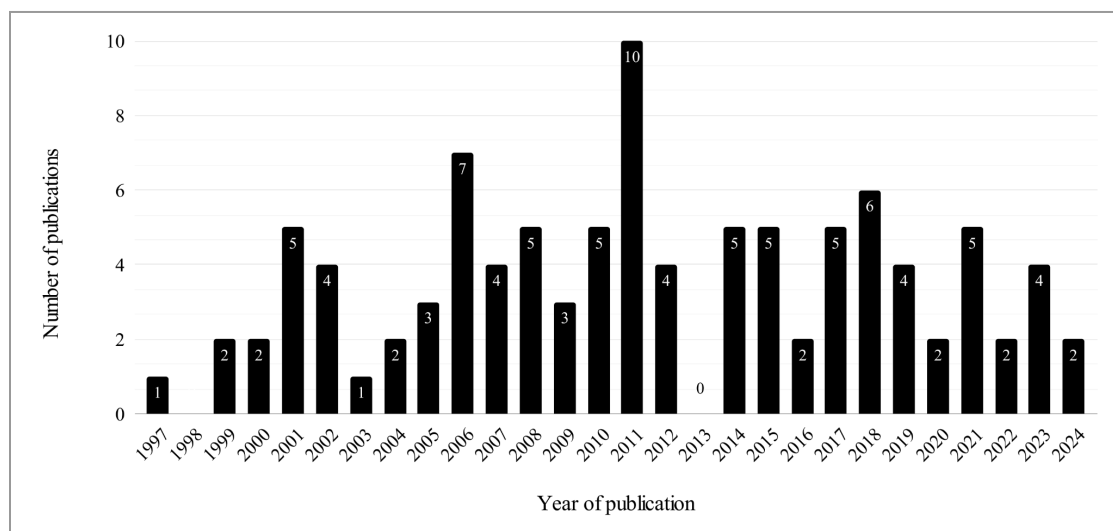


Figure 1: Number of publications per year on AI systems for ERW clearance

The State of Research Comprises Two Main Streams

The review reveals that research on AI systems for ERW clearance operations can be grouped into two main streams (see Figure 2). More than 90% of the publications focus on ERW object detection including research on AI systems to localize ERW during clearance operations. In contrast, a minority of the publications focus on ERW risk prediction. Risk prediction seeks to exploit patterns in data (ERW laying patterns or patterns in geographical data) to make quantified predictions for the risk of finding ERW in a region of interest to support survey and clearance operations. Both streams use different input data for the predictions.

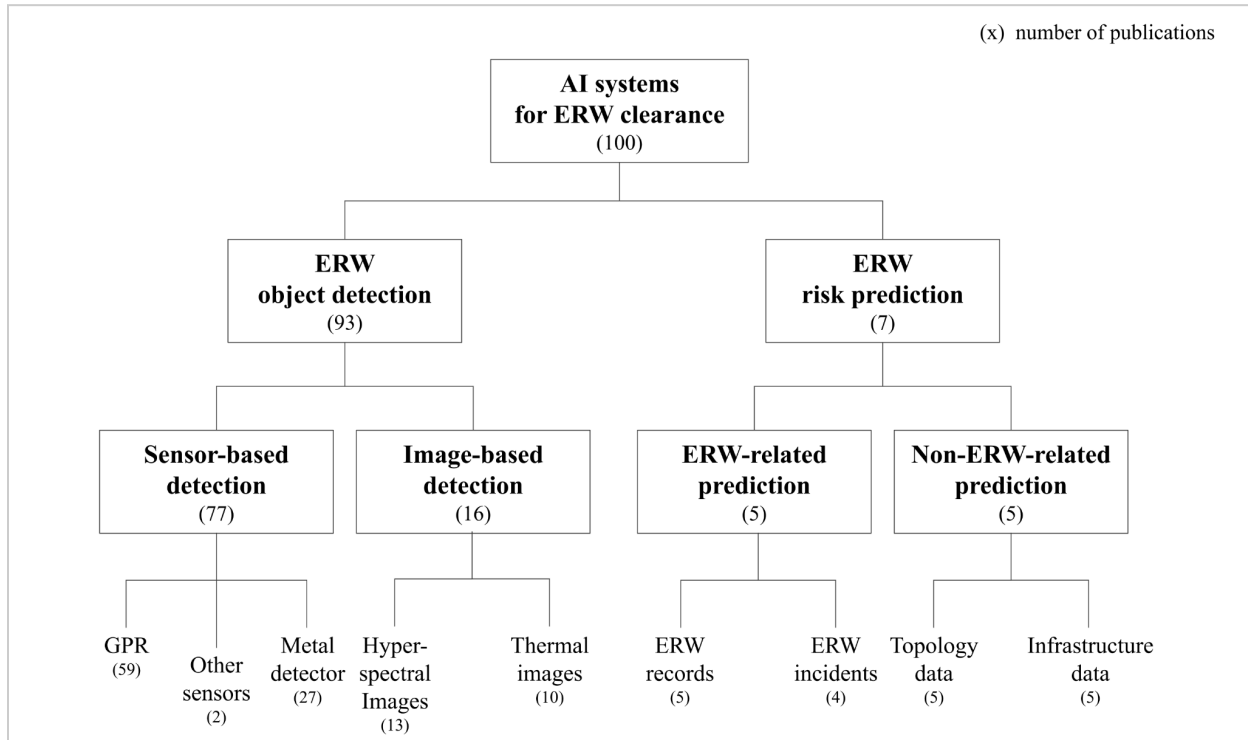


Figure 2: Research streams on AI systems to support ERW clearance

Across both research streams, a variety of AI models are developed and evaluated. In total, 30 different types of AI algorithms are used (see Figure 3). The majority of these algorithms can be divided 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 (12 publications), hidden Markov models (11 publications), and tree-based algorithms (ten publications). Understanding the AI approaches employed also helps identify potential leads for new research.

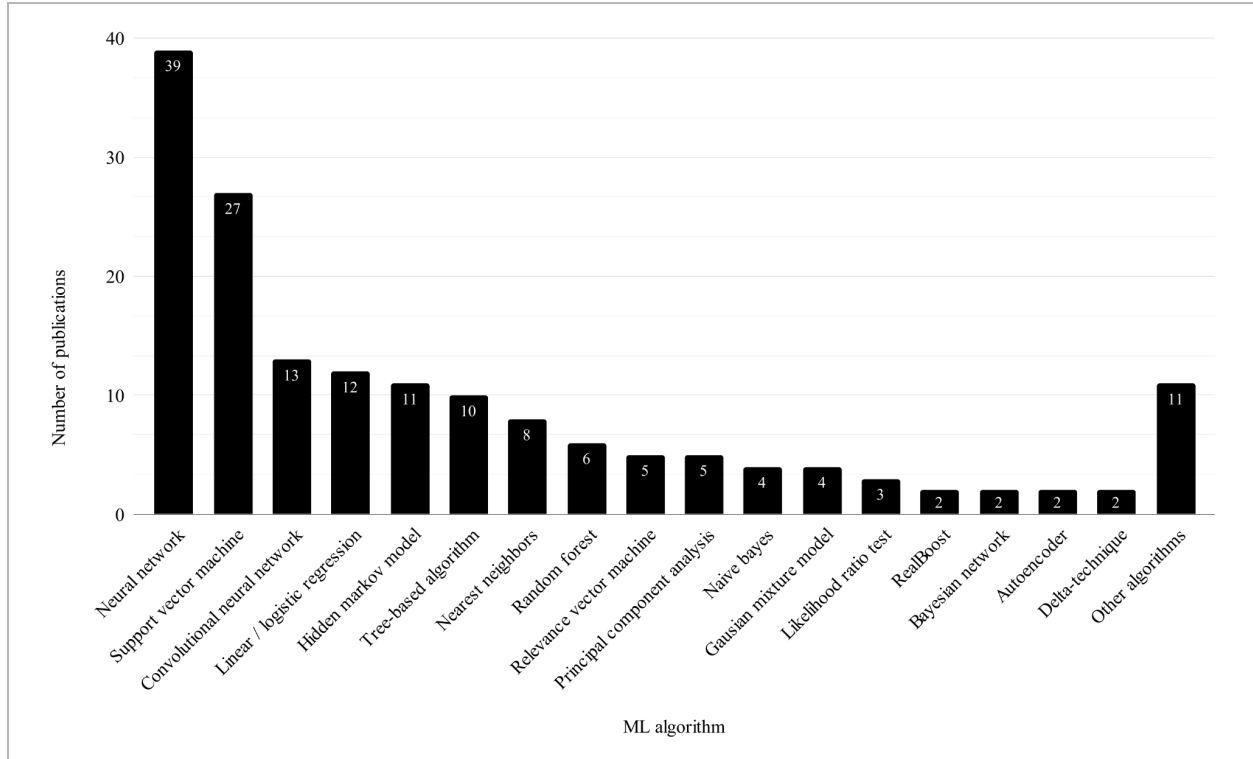


Figure 3: ML algorithms studied in research on AI systems for ERW clearance

Research Stream 1 - AI for ERW Object Detection

The majority of the research focuses on object detection. These studies cover a wide range of input data types that can be grouped into sensor data, including data from ground penetrating radar (GPR) and metal detectors, and image data, including thermal and hyperspectral image data. The researchers use AI to improve the detection of individual ERW objects from the data streams.

Most research with sensor data uses GPR data, starting with Agarwal et al. in 2001 [6]. Other authors apply AI techniques to various types of metal detectors, such as magnetometers or electromagnetic induction (EMI) sensors. They also use data from a microwave sensor, which is a cheaper alternative to a GPR sensor, or from a contact pressure sensor [7], [8]. Most commonly, these studies train support vector machines (SVM) or artificial neural networks (ANN) on the sensor data. They find that SVMs perform well in detecting different types of ERW from GPR data [9], [10], [11]. However, Bray et al. find that an ANN outperforms an SVM for ERW detection from metal detector data [12]. In general, authors find that ANNs for ERW detection from metal detector data generalize well between different test sites [13], [14], [15].

In contrast to sensor data, only 16 studies use image data. Most authors use hyperspectral imagery, such as Bolton and Gader [16], who use airborne imagery with 70 spectral responses. Others, however, use only RGB imagery, such as Baur et al. [17], who use RGB imagery acquired by unmanned aerial vehicles (UAV). Another ten researchers use infrared or thermal image data to detect both buried and surface ERW [18], [19]. Most of these publications use convolutional neural networks (CNN). The authors report high

performance with detection rates of up to 90% [17], [20]. Pre-trained CNNs are also found to perform well in this task [19], [21]. 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 [22].

Furthermore, AI-based sensor fusion for ERW object detection is analyzed by 14 authors. Most of them combine GPR and metal detector data to improve ERW object detection results, for example [6]. However, two publications combine EMI and magnetometer data to improve detection performance [23], [24]. Two other publications focus on sensor fusion of different image sensors such as RGB and thermal image data [25], [26].

Research Stream 2 - AI for ERW Risk Prediction

The second stream of research focuses on ERW risk prediction for a region of interest and includes seven publications. These authors use input data that can be divided into ERW-related and non-ERW-related data. The ERW-related data includes data from ERW records as well as from ERW incidents in the region of interest. This data is used to calculate input features for the risk prediction such as distance to the nearest ERW incident or to the front line. For example, Alegria et al. use landmine incident data to train their model [27]. 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 [28]. 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 [28], [29], [30], [31], [32]. 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 [28], [29], [30], [31], [32]. Interestingly, most publications on ERW risk prediction use a combination of ERW-related and non-ERW-related data.

All of these publications focus mainly on fundamental AI algorithms such as SVMs, tree-based, and nearest neighbor models. 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 [29]. Further, Saliba et al. compare an SVM with a random forest and a XGBoost model and find that the random forest model performs best [31]. 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 [27], [28], [30], [32], [33].

Three Opportunities for Future Research

The analysis of the eligible publications reveals several gaps in current research on AI for ERW clearance which translate into three suggested streams for future research.

First, a **renewed effort on using AI for ERW risk prediction**. New research could make significant contributions to the ability of AI to predict the risk of finding ERW at a given location, for example by identifying the most relevant input features for ERW risk prediction. In addition, research could continue to compare different ML techniques for prediction, as this has only been done by two publications. [29],

[31]. Identifying the best performing ML techniques with improved detection rates will create real world impact in the field.

Second, future research could explore the **combination of different AI systems**. From an AI perspective, both the object detection and risk prediction streams produce an estimate of the probability of finding ERW at a given location. For example, predictions from AI systems using airborne imagery could be used as input to GPR sensor data to improve false alarm rates. In addition, such systems could be improved by integrating results from AI-based ERW risk predictors that use topology and ERW-related data. For example, such risk predictions could be used to cross-check image data for false negatives. Finally, all AI systems could incorporate mine action expertise from the field, for example by incorporating prior knowledge into the prediction or by providing explanations of the predictions.

Third, the analysis reveals room for **novel approaches to improve the performance of ERW risk prediction**. For example, future research should investigate the extension of algorithms with ERW pattern information for object detection and risk prediction, as proposed by Thomas and Cathcart [22]. The authors show improvements in ERW detection by learning simple grid patterns. This approach could be extended in future research to more complex patterns and applied to ERW object detection and risk prediction.

The Future of AI for ERW Clearance

Despite the potential of AI for ERW clearance efficiency and effectiveness highlighted in this review, some researchers criticize latest efforts as “potentially hazardous, insufficiently tested, and unlikely to provide practical solutions” [34]. Thus, it is crucial to develop a fact-based view of the future of AI for ERW clearance from the findings of the literature analysis.

The rapid evolution of AI algorithms, from traditional machine learning to deep learning techniques, including large language models, means that there is a wide range of AI techniques that can be applied to ERW clearance. Although deep learning techniques are often used, many researchers report better or equal results from less complex machine learning techniques, which also allow for greater explainability. In the future, AI research for ERW clearance may split into different threads. While some will focus on applying the latest advances in AI, **traditional machine learning techniques will likely continue to play the primary role** in AI for ERW clearance. In particular, recent advances in generative AI and large language models do not fit the problem of ERW localization in clearance operations. Thus, concerns about their risks, such as those raised by Gasser [34], will have little relevance to AI for ERW clearance.

As in many fields where AI is used to enhance and de-risk human activities, **AI is likely to work hand in hand with field experts** to improve their work, as anticipated by the GICHD [35]. Fully automated ERW clearance through AI remains a distant prospect and, as this literature review shows, is unlikely to be the immediate focus of research efforts. Therefore, AI can be viewed as a useful tool for experts in the field, rather than a solution to the challenges of ERW clearance, thereby limiting the risks and responsibilities of the system.

While AI offers significant potential, it is also critical to **ensure that it is effectively integrated into real-world operations**. This requires training and testing models under realistic conditions with standardized test data to ensure comparability. Further, it requires conducting usability research to understand the needs of human operators, and incorporating prior expert knowledge to improve model robustness. In this regard, the researchers emphasize the importance of developing international funding streams that can drive collaboration between states, research institutions, and mine action programs to ensure that innovation is intrinsically linked to the specific nature and challenges of removing contamination, reducing risk, and improving lives in a region affected by ERW.

As the technology continues to advance, it is also important to remain vigilant and ensure that the development and deployment of AI is guided by ethical principles and a commitment to humanitarian goals. By addressing these challenges, AI can become a powerful tool for ERW clearance and localization, helping to save lives and accelerate the process of clearing contaminated areas.

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