

Developing Machine Learning Algorithms for Analyzing Magnetic Survey Data in Landmine Detection: From Measurement to Prediction

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Abstract: Syria faces one of the most severe landmine and explosive ordnance contamination crises globally, with over 15.4 million people at immediate risk of injury or death from explosive hazards following nearly 15 years of continuous conflict. Manual demining is successful but slow, laborious, and risky, with survey teams covering just 50–100 square meters per day. This research provides a framework for developing machine learning algorithms to interpret magnetic survey data for landmine detection, shifting from raw magnetic field measurements to predictive categorization of buried explosive hazards. This study shows that machine learning can transform magnetometry-based detection by analyzing the physical principles of magnetometry-based detection, assessing the algorithmic landscape, including Support Vector Machines (SVM), Random Forests, Convolutional Neural Networks (CNN), and unsupervised anomaly detection methods like RUDE, and evaluating Syria's pioneering drone-based magnetometer trials in November 2025. In controlled trials, SVM classifiers achieved macro-F1 scores of 0.9586 ± 0.0372 , CNN-based models achieved UXO classification accuracy above 95.8%, and deep learning approaches for magnetic data reconstruction outperformed state-of-the-art algorithms by 3–5% while operating up to 80× faster. Data scarcity for training robust models, the need for large labeled field datasets, field-deployable device computation constraints, and the near-zero false-negative requirement in safety-critical applications remain hurdles. A workflow for data collection, preprocessing, feature extraction, model training, and deployment with Syrian tweaks is presented in the paper.

Keywords: Machine Learning (ML); Magnetic Survey; Landmine Detection; UXO Classification; Convolutional Neural Networks (CNNs); Support Vector Machines (SVMs); Humanitarian Demining.

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1. Introduction

The Syrian Arab Republic is one of the most complex explosive ordnance contamination environments in the world, a consequence of nearly fifteen years of continuous conflict that has left large areas contaminated with landmines, unexploded ordnance (UXO), and other explosive remnants of war (ERW). The widespread use of explosive hazards in dynamic frontlines, urban warfare, operations for control of territory and military withdrawals has resulted in a lingering humanitarian challenge that continues to threaten civilian lives, hinder economic recovery and delay reconstruction efforts [1]. Millions of Syrians returning to areas that were previously out of reach to them face daily dangers from buried explosive devices, particularly in agricultural lands, residential areas, transportation routes and areas around critical infrastructure. While engineering and financial investment alone can solve many typical post-conflict reconstruction issues, explosive contamination is an invisible threat that requires specialized detection, mapping and clearance operations before communities can safely return to normal activities [2]. The scale and complexity of contamination in Syria clearly illustrate the need for innovative approaches that can improve the speed, safety and accuracy of humanitarian mine action [3]. Traditional landmine detection and clearance operations depend heavily on manual survey techniques, metal detectors, trained detection dogs, mechanical systems, and visual inspection.

These techniques have proved useful in many operational environments, but they remain labor-intensive, time-consuming, and carry substantial risks to personnel. Manual demining teams usually cover only small areas per day, and safety requirements, terrain conditions, environmental factors and the need for careful physical examination constrain their productivity [4]. For large contaminated areas, such as Syria, conventional methods alone cannot meet the required scale and speed of response. Moreover, traditional methods often depend on historical records, indigenous knowledge, and previously identified hazardous zones, which may be incomplete or unreliable after long-term conflict [5]. The changing nature of post-conflict environments (population movement, infrastructure reconstruction, environmental changes and land-use transformation) demands more adaptive and predictive approaches that can identify potential contamination areas before direct field intervention [6]. Among available detection technologies, magnetic surveying is one of the most promising approaches for identifying buried metallic explosive hazards. Landmines and UXO often contain large quantities of ferromagnetic materials that disturb Earth's magnetic field and produce measurable anomalies that magnetometers can detect [7]. Recent progress in sensor technology, especially uncrewed aerial vehicle (UAV)-based magnetometer systems, has opened new avenues for faster, safer large-scale surveying. UAV platforms can collect magnetic data over hazardous or inaccessible terrain while minimizing direct human exposure to contaminated areas [8].

Recent developments in drone-based magnetometer applications show potential to improve mine action operations by increasing survey coverage, reducing operational risks, and mapping magnetic anomalies at high resolution. However, converting magnetic measurements into reliable landmine predictions remains a difficult scientific and engineering problem. Many physical and environmental factors affect raw magnetic survey data, including the magnetic properties of buried objects, object size and orientation, burial depth, soil properties, sensor altitude, measurement geometry and surrounding geological variations [9]. These factors complicate magnetic signatures and increase uncertainty, making direct interpretation difficult. However, a single magnetic anomaly does not necessarily indicate a landmine or UXO. Natural geological features, metallic debris, infrastructure remnants, and environmental noise can produce similar magnetic responses. Distinguishing dangerous objects from non-threatening anomalies requires advanced analytical methods that convert raw measurements into useful predictions [10]. Machine learning (ML) has emerged as a game-changing technology in overcoming these challenges, enabling automatic pattern recognition and classification from complex datasets. Unlike traditional rule-based interpretation methods, machine learning algorithms can learn relationships between magnetic features and known object categories from historical and experimental data [11].

This ability enables ML models to detect subtle patterns that may not be apparent with standard analysis. Machine learning combines signal processing, feature extraction and predictive modeling to move from simple anomaly detection to intelligent hazard classification [12]. Magnetic anomaly analysis for landmine and UXO detection has shown considerable promise with several machine learning methods. Supervised learning algorithms such as Support Vector Machines (SVM), Random Forest (RF), and k-Nearest Neighbor (KNN) have been extensively studied because they can classify complex feature patterns in labeled training datasets. Support Vector Machines are especially useful for high-dimensional classification problems because they find optimal decision boundaries between classes. Recent studies have shown promising results of SVM-based magnetic classification with macro-F1 scores of about 0.9586 ± 0.0372 in controlled experimental settings. These results show that well-designed magnetic features, combined with strong classifiers, can accurately discriminate between hazardous and non-

hazardous targets. Random Forest algorithms offer another useful approach because they can handle non-linear relationships and high-dimensional input variables, and they provide feature-importance estimates [13].

In magnetic survey applications, Random Forest models can incorporate multiple information sources, including magnetic intensity, gradient measurements, spatial characteristics, and environmental variables. Their interpretability and robustness make them especially attractive for operational applications where understanding of model decisions is essential for safety-critical humanitarian operations [14]. Recent advances in deep learning have opened up even more possibilities for automated interpretation of magnetic data. Convolutional Neural Networks (CNNs) were originally designed to handle image identification tasks and have been used to analyze magnetic anomaly maps and spatial representations of sensor data [15]. CNN-based models can automatically learn hierarchical features from raw or minimally processed magnetic measurements, reducing dependence on manually designed feature extraction methods. Deep learning techniques for UXO classification have achieved accuracy above 95.8%, indicating that neural networks can learn complex relationships between magnetic signatures and buried objects. In addition, the latest deep learning techniques for magnetic data reconstruction and enhancement achieve 3–5% higher accuracy and run much faster than previous state-of-the-art algorithms [16]. Despite the success of supervised machine learning methods, one of the biggest issues in landmine detection is the dearth of labeled training data. Real humanitarian environments lack documented cases of buried explosive devices, as training data necessitates controlled testing, excavation, or operational encounters [17]. This creates a severe imbalance between hazardous and non-hazardous samples and limits traditional supervised algorithms' ability to generalize across different geographical environments.

Therefore, unsupervised and semi-supervised learning methods are an important research direction [18]. Techniques such as RUDE (Rapid Unsupervised Detection of Events) can identify anomalous magnetic patterns without extensive labeled datasets. These approaches are particularly useful in conflict-affected areas such as Syria, where obtaining complete ground-truth datasets is still challenging. Combining machine learning with UAV-based magnetic surveys is a major step forward for next-generation humanitarian demining systems. UAV platforms can quickly collect large amounts of spatially distributed magnetic data. Machine learning algorithms can process these datasets to identify potential contamination zones and prioritize field investigations [19]. Such systems could help shift from reactive clearance, where teams respond only after contamination is detected, to predictive risk management, where risks are identified before they cause harm. This transition matters for Syria, where contamination exceeds the capacity of conventional clearance methods, and resources must be deployed strategically. However, many challenges must be addressed before machine learning-based magnetic detection systems can be deployed widely [20]. The first challenge is data availability. Reliable models require datasets that cover a range of soil conditions, device types, burial depths and environmental contexts. Models trained under controlled laboratory conditions may perform worse in complex field environments. The second challenge is computational [21]. While cloud-based processing can support more sophisticated models, field operations often require lightweight systems to make rapid decisions in remote areas with limited connectivity. The third and most important challenge is safety and reliability.

They can have catastrophic consequences in humanitarian demining. Therefore, model development should focus on reliability, uncertainty estimation, and rigorous validation, not just accuracy [22]. The situation in Syria is difficult, but it also provides a unique setting to apply machine learning to magnetic survey analysis. The country's large-scale contamination problem creates an urgent need for innovative solutions, and recent advances in drone technology, artificial intelligence and geospatial data management provide the technological basis for developing such systems. Syria's nascent interest in trials of drone-based mine detection reflects an awareness of the need for modern approaches to humanitarian clearance [23]. Integrating UAV magnetometry, advanced signal processing, and machine learning algorithms can help Syria develop a more efficient, safer framework for assessing explosive hazards. This work explores developing machine learning algorithms to analyze magnetic survey data for landmine detection, from data acquisition to predictive classification. It examines the physical basis of magnetic anomalies; assesses current algorithmic approaches (SVM, Random Forest, CNN, and unsupervised anomaly detection); and develops a comprehensive analytical framework for Syria's operational environment. This research aims to contribute toward safer, faster and more intelligent humanitarian demining operations by addressing challenges in data pre-processing, feature engineering, model selection, validation and deployment [24]. The findings are also relevant beyond Syria, offering lessons for other conflict-affected areas seeking to leverage artificial intelligence and remote sensing technologies to speed up land release, enhance civilian protection and mitigate the long-term humanitarian impact of explosive contamination [25].

2. Literature Review

The disturbing effect of the ferromagnetic materials in landmines and unexploded ordnance (UXO) on the Earth's magnetic field has been widely studied as an effective geophysical method for detecting buried metallic explosive hazards. Early work showed that magnetic anomalies induced by buried objects can provide useful information about the target's location and nature. Interpretation is difficult because object properties, burial conditions, soil magnetism and environmental noise vary. Recent studies have therefore focused on combining advanced signal processing and machine learning techniques to improve detection reliability and automate anomaly interpretation [13]; [8]. Magnetic detection models buried metallic objects as magnetic

dipoles. The magnetic moment, object size, material composition, depth and orientation control the strength and spatial distribution of magnetic anomalies. Magnetic gradient tensor approaches offer better target localization because they measure spatial variations in the magnetic field rather than absolute magnetic intensity. Recently, Zheng et al. [13] showed that magnetic gradient tensor methods may improve parameter estimation and detection accuracy for UXO targets, particularly in shallow environments where localization accuracy is essential. Thus, advanced gradiometry has become an important component in modern magnetic survey systems for humanitarian demining applications. The development of UAV-borne magnetometer systems has significantly improved the operational capability of magnetic surveys. UAV platforms allow rapid data acquisition over large, dangerous or inaccessible areas without putting human operators at risk.

Yoo et al. [20] demonstrated the effectiveness of UAV-based magnetometer surveys for mine detection in the Korean Demilitarised Zone, successfully detecting magnetic anomalies associated with metallic landmines. Yoo et al. [1] also presented a machine learning classification framework for UAV-borne magnetometer data, demonstrating how artificial intelligence techniques can be effectively integrated with magnetic measurements from aerial platforms for automated target identification. Recent operational developments, such as Syria's November 2025 trial of drones for landmine detection, further emphasize growing interest in integrating UAV technology with advanced analytical methods for humanitarian mine action [15]. One of the principal challenges reported in the literature is that raw magnetic measurements have high uncertainty due to geology, sensor noise, environmental interference and variations in target characteristics. Traditional manual interpretation methods require expert knowledge and do not scale well to large contaminated regions. Researchers have increasingly turned to machine learning algorithms that can automatically extract complicated patterns from magnetic datasets to overcome these limitations. Supervised learning methods such as Support Vector Machines (SVM), Random Forest and hybrid classification models have been proven effective in differentiating landmine-related anomalies from non-hazardous signals. Recently, Yilmaz et al. [2] proposed a hybrid passive mine detection and classification approach based on magnetic signatures and demonstrated the potential to improve detection performance through machine learning-assisted classification. Recently, SVM-based approaches have also achieved high classification performance, reporting macro-F1 scores over 0.95 under controlled experimental settings [1].

Deep learning approaches have advanced magnetic anomaly interpretation by enabling automated feature extraction from raw or minimally processed data. Convolutional Neural Networks (CNNs) have been particularly useful because they can recognize spatial patterns in magnetic anomaly maps. Lytvyn et al. [3] used convolutional neural networks for passive mine detection based on magnetic field data and showed better classification performance than traditional methods. Likewise, Peleshchak et al. [4] investigated how neural network architecture affects mine detection performance, highlighting the importance of network design for robust classification. Researchers have applied deep learning to UXO recognition using electromagnetic and magnetic datasets, with studies reporting classification accuracies above 95% [8]; [7]. These results demonstrate neural networks' potential for safety-critical detection applications. Beyond supervised learning, the lack of labeled mine-detection datasets has also drawn attention to unsupervised and semi-supervised approaches. Confirmed instances of buried mines are rare in real humanitarian operations, making it difficult to build large training datasets. Other approaches include unsupervised anomaly detection techniques such as RUDE (Rapid Unsupervised Detection of Events), which can detect unusual magnetic patterns without requiring large amounts of labeled data. These approaches are especially important in post-conflict situations, such as Syria, where contamination data are incomplete and difficult to validate in the field [10]. More recent work has also explored multi-modal data fusion approaches that combine magnetic measurements with complementary sensing technologies. Integrating magnetometer data with ground-penetrating radar (GPR), electromagnetic induction (EMI), thermal imaging and multispectral sensors has shown potential to improve detection reliability by reducing ambiguity between hazardous targets and background anomalies.

Kuru et al. [9] showed that fusing magnetometer and GPR data can improve automated airborne ordnance detection. García-based and electromagnetic studies have shown the benefits of fusing multiple sensing modalities for improved target discrimination. Such techniques are especially useful in complex environments where individual sensors may produce uncertain results. Despite substantial progress, several research gaps remain. The shortage of high-quality labeled field datasets remains a key limitation to developing robust ML models. Transferring models trained in controlled environments to real operational settings often degrades performance because soil properties, sensor configurations, and target characteristics vary. Further, in humanitarian demining, false negative rates must be very low, since failing to detect a hazardous object can cause civilian casualties. Future systems therefore need to focus on reliability, uncertainty estimation and operational validation rather than accuracy. UAV-based magnetometry and machine learning offer a promising route to safer, more efficient explosive hazard assessment in Syria. Current research shows that artificial intelligence can turn magnetic survey data from basic anomaly observations into predictive information to prioritize clearance operations. However, data collection, model adaptation, computational efficiency, and integration into humanitarian mine action workflows pose challenges to successful implementation. The current literature provides a strong basis for developing an end-to-end machine learning setup that combines magnetic data collection, processing, feature extraction, classification and operational deployment to enable faster landmine detection in Syria and other conflict zones.

2.1. The Transition from Manual to Machine Learning-Based Detection

Traditional landmine detection has relied on manual methods using metal detectors and prodding techniques. These methods are effective but exceedingly slow, labor-intensive, and dangerous. The average manual deminer covers approximately 50–100 square meters per day, making large-scale clearance a multi-year or even multi-decade undertaking. Applying machine learning to magnetic survey data represents a paradigm shift in landmine detection. As one comprehensive dissertation noted, "machine learning techniques, particularly convolutional neural networks (CNNs), serve as robust target detection and parameter estimation tools." By "synergizing multiple geophysical modalities, these methods enhance our ability to discern subtle anomalies with high accuracy." The transition from measurement to prediction involves several key steps:

- **Data Acquisition:** Collection of magnetic field measurements via ground-based or UAV-mounted magnetometers.
- **Preprocessing:** Noise reduction, filtering, and correction for environmental variations.
- **Feature Extraction:** Identification and characterization of magnetic anomalies.
- **Classification:** Application of machine learning models to distinguish landmines from clutter.
- **Prediction:** Generation of probability maps indicating likely mine locations.

The literature on machine learning for magnetic anomaly detection has evolved significantly, with a large variety of methods and methodologies being explored. Support Vector Machine (SVM) classifiers have been shown to perform well in magnetic anomaly categorization. In a detailed investigation by Yoo et al. [1] and colleagues, five machine-learning models were tested on data from a UAV-based magnetometer, and the SVM achieved the best macro-F1 score of 0.9586 ± 0.0372 , with no confusion between landmines and debris in hold-out testing. The study also included percentile distance as a new parameter to characterize signal attenuation. It showed that selected percentile distances improved macro-F1 scores for all examined models compared with the full percentile range. Convolutional Neural Networks (CNNs) have also been shown to be effective for UXO classification using magnetic and electromagnetic induction data. Researchers have constructed CNN models for UXO classification directly from EMI data, trained on synthetic datasets generated by dipole forward models that account for key UXO and clutter elements. A deep learning approach for UXO type recognition based on magnetic detection has achieved over 95.8% accuracy and an F1-score above 92.5% for three simulated UXO target types. The approach achieved over 85.9% accuracy and an F1-score above 81.1%, even with interference. Recent work on CNN architectures for magnetometer-based UXO classification has also compared custom CNN models with traditional machine-learning approaches such as Random Forest and k-Nearest Neighbors (kNN). These studies have addressed limited training data by using high-fidelity digital twins to create complete datasets of magnetometer signals from UXO and non-UXO objects, including complex remanent magnetization effects.

Under tough classification settings, CNN models have obtained balanced accuracies around 84.65%. Beyond classification, deep learning has been used to reconstruct dense magnetic maps from sparsely sampled gradiometer data. A 2026 study showed a deep learning-based solution that was more accurate and faster than traditional interpolation techniques, attaining an average reconstruction-accuracy gain of 3–5% and operating up to 80 times faster than current algorithms. Researchers have also investigated unsupervised anomaly detection, e.g., the Rapid Unsupervised Detection of Events (RUDE) algorithm, which uses principal component analysis (PCA) combined with unsupervised clustering using a One-Class Support Vector Machine (OC-SVM) to detect anomalies in magnetometer time-series data. This technique enables landmine detection without prior assumptions about UXO type [2]. Hybrid sensor-fusion techniques that combine multiple geophysical data types have also shown potential. For instance, the MagEMNet framework uses a convolutional neural network to incorporate electromagnetic and magnetic data and improve subsurface target detection. Research on sensor fusion has shown that fused classifiers can outperform classifiers based on GPR or EMI characteristics alone. Syria has become a Middle East pioneer in using drone-based magnetometer surveys to detect landmines. On 16 November 2025, the Syrian Ministry of Emergency and Disaster Management, through its National Mine Action Center (NMAC), carried out the first practical test of an advanced German-made drone specifically specialized for landmine detection in the Drousha region of the Damascus countryside. The drone, supplied by a German company called Setera, has a magnetometer system that can identify landmines, unexploded ordnance and other conflict artifacts up to six meters below the Earth's surface. The device can also estimate the weight and depth of identified items and operate at speeds up to 8 km/h.

In the test, the drone surveyed about 10,000 square meters in about 35 minutes. The testing showed the ability to identify contaminated objects accurately and provide information on their weight, depth and size, said Hussam Hallak, deputy minister of emergency and disaster management. Magnetometer technology detects mines, unexploded ordnance and other conflict artifacts up to six meters below the surface. The trial's success has established Syria as a regional leader in using advanced detection technology. Humanitarian organizations working in Syria have also begun using modern tools, including drones and machine-learning algorithms, to speed detection activities [3]. But Fadi al-Saleh, director of the National Mine Clearance Center, said the sustained success of such efforts depends on having enough drones, continuous personnel training and expected international support for humanitarian demining activities. The literature increasingly explores these elements individually, and

drones are increasingly used to survey the Syrian context. Still, such analysis is lacking, especially integrated from the ground up (i.e., from raw magnetic measurements to predictive classification) and tailored to developing machine-learning algorithms for magnetic survey data in Syria. This paper fills this gap by giving a comprehensive algorithmic framework for machine-learning-based interpretation of magnetic survey data. The methodology draws on magnetometry principles, recent advances in machine learning for UXO classification, and the operational realities of drone-based surveys in Syria. The proposed paradigm integrates these elements to provide practical guidance for researchers, practitioners, and policymakers seeking to use machine learning to accelerate and improve the safety of humanitarian demining in Syria and other conflict-affected areas.

3. Methodology

3.1. Research Design and Data Sources

This work examines machine learning approaches for analyzing magnetic survey data to detect landmines and unexploded ordnance (UXO) using a mixed-methods research methodology that includes a systematic literature review, algorithmic analysis, case study investigation and comparative assessment. The methodology combines theoretical knowledge of magnetic anomaly generation with the practicalities of UAV-based magnetometer surveys, machine-learning classification, and operational deployment within the framework of humanitarian mine action. The research is based on primary and secondary data. Main sources include peer-reviewed studies on magnetic anomaly detection, UXO classification and machine learning applications; technical reports on drone-based magnetometer trials in Syria; and operational experience from humanitarian mine action organizations (Figure 1).

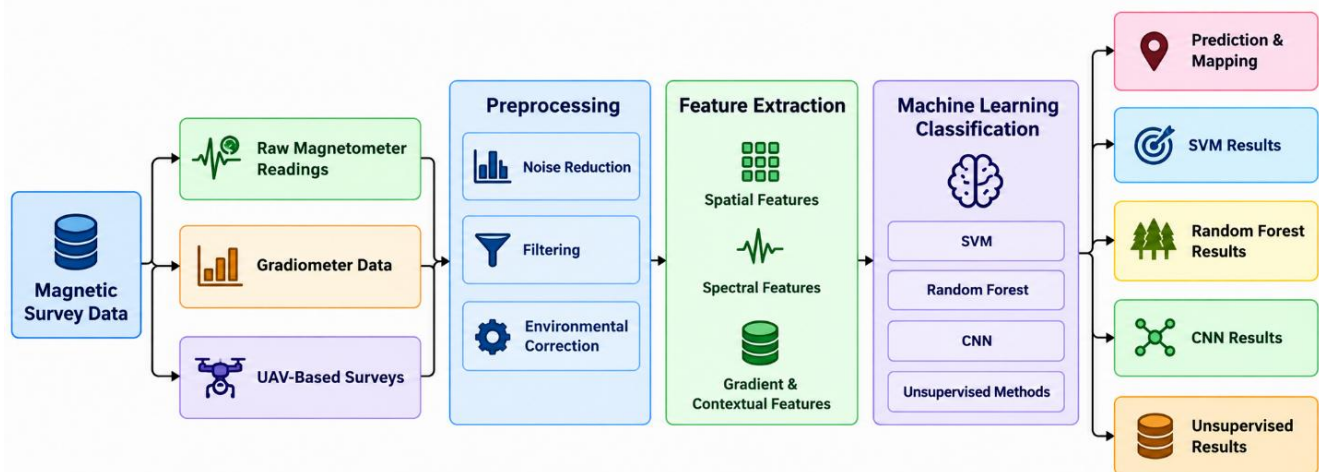


Figure 1: Overview of the machine learning pipeline for magnetic survey data analysis

Secondary sources include academic databases such as IEEE Xplore and Springer, open-source machine learning repositories, and relevant studies summarizing current breakthroughs in drone-assisted mine-detecting technology. The study also lists selected case studies, such as the Setera drone trial in the Damascus countryside in November 2025, the RUDE algorithm for unsupervised magnetic anomaly detection, SVM-based classification approaches using UAV magnetometer data, and CNN-based UXO classification methods based on electromagnetic induction (EMI) data. These cases provide comparative insight into distinct machine learning strategies, data needs and practical restrictions.

3.2. Analytical Approach

The analytical framework evaluates machine learning-based magnetic detection systems across five interrelated dimensions. First, the study reviews the physical basis of magnetic anomaly detection, including the relationship between buried metallic objects, magnetic field disturbance and measurable sensor response. Second, the study covers data acquisition and preprocessing methods, including UAV survey techniques, sensor technologies, noise reduction, correction procedures, and preparing magnetic datasets for machine learning applications. Third, the study discusses feature engineering methods for extracting relevant predictive information from magnetic data, including spatial, spectral, gradient and contextual features. Fourth, the study evaluates algorithm selection and model-training strategies by comparing supervised, unsupervised, and deep learning approaches for anomaly classification and localization. Finally, the authors discuss deployment and operational considerations, including computational needs, field applicability, integration with humanitarian mine action workflows, and

safety-critical constraints associated with real-world implementation. This framework provides a structured pathway for evaluating the feasibility of applying machine learning-based magnetic survey analysis for landmine detection in Syria and other conflict-affected environments.

3.3. Physical Foundations: From Magnetic Fields to Anomalies

3.3.1. The Physics of Magnetic Anomalies

The Earth's magnetic field provides a natural background against which buried ferromagnetic objects create detectable disturbances. When a ferromagnetic object, such as a metallic landmine or unexploded ordnance, is buried in the ground, the Earth's field magnetizes it, creating a secondary magnetic field that adds to or subtracts from the ambient field (Figure 2).

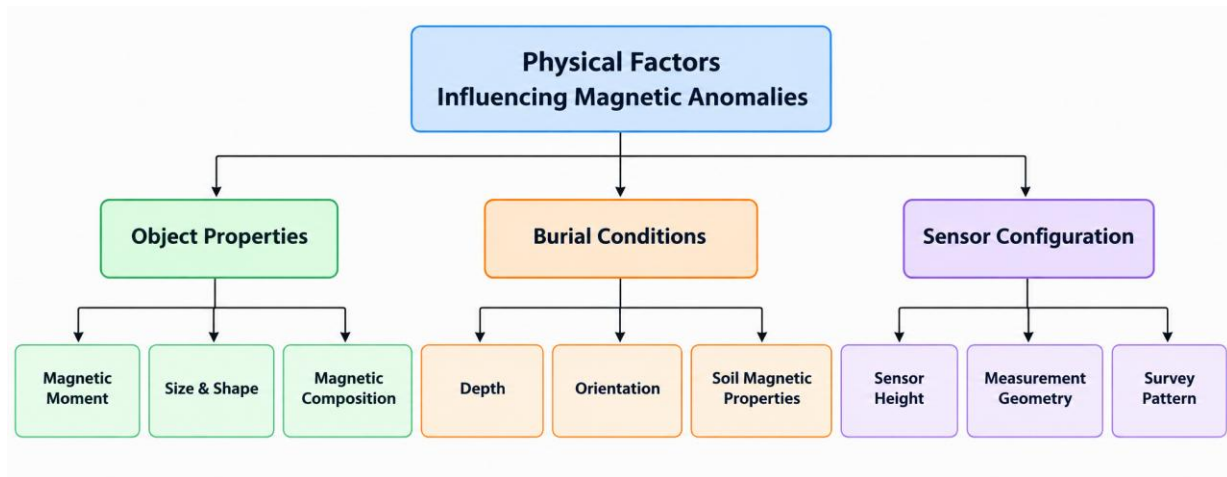


Figure 2: Physical factors influencing magnetic anomalies

The resulting magnetic anomaly can be modeled mathematically as a magnetic dipole. For a dipole at position r_0 with magnetic moment m , the magnetic field B at observation point r is given by:

$$B(r) = (\mu_0/4\pi)[3(m \cdot R)R/R^5 - m/R^3] \quad (1)$$

Where:

$$R = r - r_0 \text{ and } R = |R| \quad (2)$$

This dipole model underpins both classical inversion techniques and modern machine learning approaches. The anomaly's characteristics—amplitude, shape, and spatial extent—depend on several factors:

- **Object Properties:** Magnetic moment, size, shape, and material composition
- **Burial Conditions:** Depth, orientation, and surrounding soil magnetic properties
- **Sensor Configuration:** Height above ground, orientation, and measurement geometry

3.3.2. Magnetic Gradiometry and Its Advantages

Magnetic gradiometry, which measures the spatial gradient of the magnetic field, offers significant advantages over total-field magnetometry for landmine detection. The magnetic gradient tensor, containing the nine spatial derivatives of the three magnetic field components, provides richer information about subsurface sources. The finite-difference magnetic gradient tensor (FDMGT) has been shown to play a "pivotal role in precise target localization and parameter estimation". Gradiometer measurements are less sensitive to temporal variations in the Earth's magnetic field (such as diurnal variations and magnetic storms) and to regional magnetic gradients, making them particularly suitable for detecting small, localized anomalies from buried objects. Recent research has focused on developing "a novel triaxial magnetic gradiometer" that "overcomes the deficiencies of single-sensor systems, demonstrating superior sensitivity to small-scale variations in the magnetic field". These advances in sensor technology, combined with UAV platforms, have dramatically expanded the capabilities of magnetic surveys for humanitarian demining. Choosing the right sensor technologies and survey platforms is key to successfully

acquiring magnetic survey data. Magnetometers are the most common sensors for measuring magnetic-field fluctuations, and different types offer varying sensitivity and measurement capabilities. Fluxgate magnetometers are commonly employed for delicate vector measurements, where the magnitude and the direction of the magnetic field are critical. Optically pumped magnetometers typically produce scalar magnetic-field measurements and offer very high sensitivity (Figure 3).

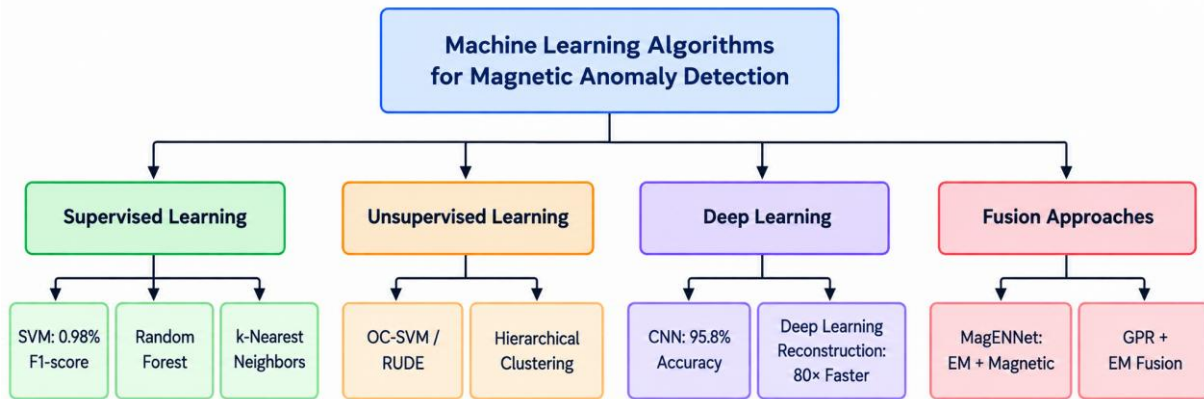


Figure 3: Taxonomy of machine learning algorithms for magnetic anomaly detection

Superconducting quantum interference devices (SQUIDs) are highly sensitive and can detect very small magnetic-field differences. Still, their operational needs may make them less practical for field-based humanitarian assessments. Gradiometers provide information on spatial variation of the magnetic field. They can be configured in several forms: single-axis gradiometers that measure one gradient component, tensor gradiometers that measure multiple gradient components, and triaxial gradiometers that provide measurements needed to estimate the full magnetic-gradient tensor. These sensor technologies can be implemented on different survey platforms depending on the topography, survey requirements and operational conditions. Ground-based platforms might be hand-carried systems, vehicle-towed sensors, or robot-mounted equipment. Airborne platforms can be uncrewed aerial vehicles (UAVs) or helicopters. UAV-based systems are particularly promising for hazardous or hard-to-reach areas, as they can take magnetic measurements while avoiding personnel on potentially contaminated land. Previous studies have integrated magnetometer systems into UAV platforms to detect metallic antipersonnel landmines. These systems have successfully detected various magnetic anomalies associated with metallic objects. Therefore, combining sensitive magnetic sensors, appropriate gradiometer configurations, and UAV-based platforms offers a versatile, potentially safer alternative for acquiring high-resolution magnetic survey data in mine-damaged and conflict-affected situations.

4. Results

Designing effective magnetic surveys for landmine detection is difficult and requires careful consideration of survey design factors such as line spacing, flying height, survey speed and coverage patterns. The spacing directly controls the spatial resolution of the acquired magnetic data. Tighter line spacing improves spatial resolution and increases the ability to detect minor or closely spaced anomalies, but it adds survey time and operational demands. Line spacing of ~1 to 5 m is generally appropriate for UAV magnetic surveys, depending on survey purpose, terrain, sensor attributes and projected target size. Flight height is also crucial, as the sensor's altitude above the ground directly affects anomaly amplitude and spatial resolution. The lower the flight height, the stronger the magnetic response and the better the detection of shallow targets. But the lower the flight height, the greater the chance of collision with foliage, buildings, terrain irregularities and other objects. Survey speed also affects data quality, since higher speeds may reduce measurement density and the signal-to-noise ratio. For example, the Setera drone can travel up to 8 km/h, scanning nearly 10,000 square meters in 35 minutes. Magnetic surveys are typically carried out on a fixed grid or mowing pattern. This ensures systematic coverage and avoids leaving areas unsampled. Raw magnetometer measurements need substantial pre-processing before they may be used effectively in machine learning analysis.

The first major step is noise reduction, which identifies and removes instrumental noise, ambient interference, electromagnetic disturbances and other undesired components from the recorded magnetic signal. Recent developments in AI-based denoising and interpolation of magnetic unexploded ordnance (UXO) data have shown 3-5 % greater reconstruction accuracy while running up to 80 times faster than some state-of-the-art techniques. Such techniques are particularly relevant for UAV-based surveys, since airborne sensors face additional interference from aircraft electronics, motors, vibration and movement. Another important pre-processing step is diurnal correction, which removes temporal variation in Earth's magnetic field during a survey. This is normally achieved by correlating survey magnetometer data with data from a fixed base-station magnetometer and

removing the resulting temporal fluctuation. After rectification, researchers can grid and interpolate irregularly spaced magnetic observations onto a regular spatial grid. Regularized magnetic maps suit machine learning algorithms such as convolutional neural networks because they provide image-like representations that respect spatial interactions between measurements. Researchers have also explored deep learning methods to interpolate and reconstruct magnetic data. Further preprocessing might include removing regional magnetic gradients unrelated to buried objects (Figure 4).



Figure 4: Data preprocessing pipeline for magnetic survey data

Large-scale geological differences can produce magnetic trends across the survey region, masking smaller abnormalities caused by mines or UXO. Polynomial fitting, median filtering, detrending and other background-removal techniques can then be used to pinpoint localized anomalies. UAV motion may also generate motion-related artifacts in magnetic measurements. Artificial variations can arise from changes in orientation, altitude, acceleration, vibration, or sensor proximity to the UAV platform and may be misidentified as targets. Thus, techniques to identify and mitigate magnetic self-noise in UAV-mounted gradiometers are vital to improve data fidelity and spatial coherence (Figure 5).

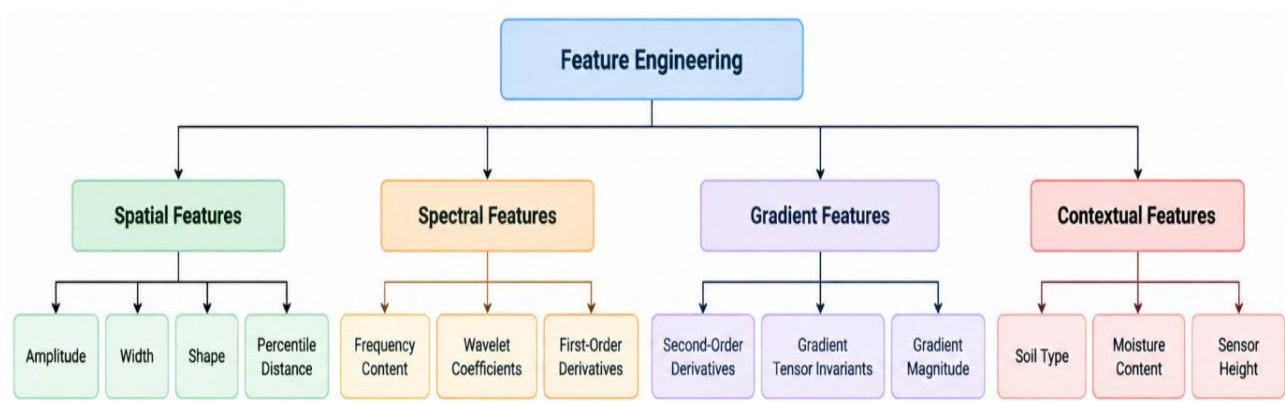


Figure 5: Feature engineering framework for magnetic anomaly detection

Therefore, effective preprocessing should produce a rectified and normalized dataset in which environmental, instrumental, temporal and motion-related effects have been eliminated before feature extraction and classification. The Syrian operational environment presents several data challenges for ML-based mine identification. One of the most important challenges is data

scarcity. Research has highlighted insufficient training data as a major problem for developing robust machine learning algorithms for UXO classification using magnetometer measurements. This is especially a problem in Syria, where long-term conflict and instability have prevented rigorous monitoring, gathering and documentation of the contaminated areas. The lack of reliable labeled measurements limits training supervised algorithms that can reliably discriminate mines, UXO, metallic debris, and naturally occurring magnetic anomalies. One key problem is that survey conditions differ across Syria's 14 governorates. Thus, a model trained in one geographical context may perform poorly in another unless the training dataset reflects sufficient environmental diversity. Moreover, infrastructure limitations challenge UAV-based machine learning systems.

The GPS instability and weak internet connectivity during the November 2025 drone experiment can impact aircraft navigation, georeferencing, data synchronization, and real-time processing. The restrictions suggest that a reliable operating system should not rely solely on constant cloud connectivity. Field operations may therefore require local storage, offline processing, robust positioning systems, and edge computing capabilities. Another major difficulty is the heterogeneous nature of contamination in Syria. Surveyed locations may contain antipersonnel mines, anti-tank mines, improvised explosive devices (IEDs), unexploded ordnance (UXO), abandoned munitions, metallic shards, building debris and other ferrous objects. These targets can produce varied magnetic signatures based on their material composition, geometry, orientation, burial depth and surrounding environment. Therefore, a machine learning system should distinguish dangerous objects from benign metallic debris while accounting for uncertainty in the available ground-truth data. Feature engineering is an important step in developing machine learning systems for magnetic anomaly detection, since input representation quality directly affects classification performance, especially when training data is limited (Figure 6).

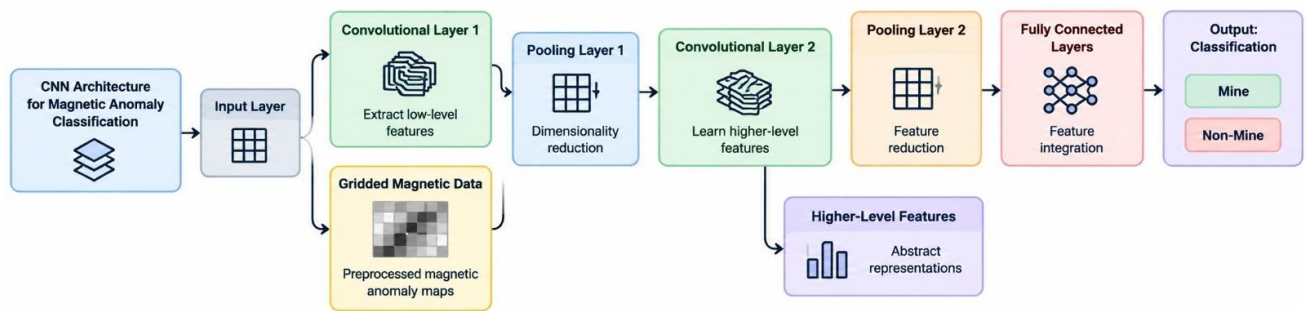


Figure 6: CNN architecture for magnetic anomaly classification

Recent work shows that input feature selection can significantly affect the effectiveness of data-driven landmine detection models. One example is percentile distance, the distance at which an anomaly drops to a given percentage of its greatest amplitude. Studies have shown that adding these characteristics improves macro-F1 scores across several machine learning algorithms. Spatial features may include anomaly amplitude (the maximum deviation of the magnetic field), anomaly breadth (the spatial extent of an anomaly), and shape aspects such as symmetry, gradient, and curvature. Percentile distances calculated at different thresholds can further inform the spatial decay of magnetic responses and may help distinguish between target configurations. Another representation of magnetic anomalies is spectral features that describe the signal's frequency characteristics. In the frequency domain, these may include wavelet transform components and power spectral density estimates. Gradient-based features are particularly important as buried items tend to generate localized spatial fluctuations in the magnetic field. First derivatives can characterize magnetic gradients, and second derivatives can provide information on curvature and local changes in the field. The gradient tensor components and their invariants can provide further information on geometry and spatial organization of magnetic anomalies. Using contextual data such as soil type, soil wetness, sensor height, terrain characteristics, and survey conditions can further improve classification. These contextual variables allow machine learning algorithms to account for environmental factors that influence the measured magnetic response (Table 1).

Table 1: Comparative performance of machine learning and deep learning algorithms for UXO detection

Algorithm	Performance Metric	Context	Reference
SVM	Macro-F1: 0.9586 ± 0.0372	UAV magnetometer data, 43 buried targets	Yoo et al. [1]
CNN	Accuracy: >95.8%, F1: >92.5%	UXO magnetic detection	Wen et al. [8]

CNN	Balanced Accuracy: 84.65%	UXO classification with digital twin	Ściegienka and Blachnik [14]
RUDE (OC-SVM)	Unsupervised anomaly detection	Magnetometer time series	Hoffmann et al. [21]
Deep Learning Reconstruction	3-5% higher accuracy, 80× faster	Magnetic data interpolation	Kovalenko et al. [10]

Magnetic surveys provide high-dimensional data with many correlated features; therefore, feature selection is needed to improve computational efficiency and reduce overfitting risk. Filter methods rank features by statistical criteria such as correlation, mutual information or other relevance metrics and do not depend on a specific machine learning model. Wrapper approaches may use forward selection, backward elimination or recursive feature elimination, using model performance to evaluate different feature subsets. Embedded approaches perform feature selection during model training. One technique to reduce the effect of less informative variables is L1 regularization. Domain knowledge is also critical, since physical insight into magnetic anomalies can help identify features meaningfully related to buried objects. In safety-critical applications, it is desirable to combine statistical feature selection with physical interpretation rather than rely solely on automated feature-ranking algorithms. Among the traditional machine learning methods, Support Vector Machines (SVMs) have been shown to perform well in magnetic anomaly categorization. SVM seeks the optimal decision boundary that separates classes in the feature space while maximizing the margin between them. Its main advantages are its effectiveness in high-dimensional feature spaces, memory efficiency and adaptability with multiple kernel functions. Five standard ML models were evaluated, and SVM earned the greatest macro-F1 score of 0.9586 ± 0.0372 without confusion between landmines and debris in hold-out testing. However, in practice, you must choose the right kernel (e.g., linear, polynomial or radial basis function) and carefully tune the C and gamma parameters. Because mine-detection datasets may contain far more non-target observations than verified mines, solutions for controlling class imbalance are particularly important.

Random Forest is another suitable alternative because it combines multiple decision trees and produces classification or regression outputs based on the collective predictions of the individual trees. This approach is typically robust to overfitting, can handle high-dimensional datasets, is highly resistant to outliers, and may provide estimates of feature relevance. Magnetic anomaly classification has been compared across Random Forest, SVM, k-nearest neighbors, Decision Trees and Gradient Boosting, with optimized feature sets improving accuracy and reducing the rate of undetected landmines across the examined models. Key implementation factors include the number of trees, maximum tree depth and feature-sampling approach. Random Forests may be especially useful in the early phases of Syrian model building because they provide interpretable information about feature relevance and require less training data than many deep learning algorithms. Convolutional Neural Networks (CNNs) have been a powerful tool for UXO classification using magnetic and electromagnetic induction data, especially when measurements are translated into regular spatial grids or image-like representations. CNNs can automatically learn spatial features hierarchically from magnetic maps and discover patterns that are difficult to define with manually designed features. Their main advantages are automatic feature extraction, the ability to capture both local and global spatial patterns, and strong performance on image-based classification tasks. Deep learning methods for UXO type recognition using magnetic detection data have been reported to reach accuracies above 95.8% and F1-scores above 92.5%. At the same time, CNN-based models applied to electromagnetic induction data have attained balanced accuracies of ~84.65%. However, CNN architectures typically require much larger and more diverse training datasets than traditional machine learning techniques. Key architectural choices include the number of convolutional layers, filter size and count, pooling strategy, activation functions, dropout or other regularization methods, and the size of the input magnetic-data window.

When labeled training data is insufficient, unsupervised anomaly detection can be a feasible alternative. Unsupervised approaches identify observations that differ from the dominant background pattern rather than learning preset classes from labeled instances. This approach is highly applicable to Syria, since many contaminated locations may lack credible ground-truth information. For example, the Rapid Unsupervised Detection of Events (RUDE) technique uses Principal Component Analysis (PCA), unsupervised clustering and a One-Class Support Vector Machine (OC-SVM) to find anomalies in magnetometer time-series data. This method can help locate landmines without assuming the type of UXO present beforehand. Other clustering methods, such as hierarchical clustering of filtered magnetic-gradient data, can suggest subregions for further examination, where techniques such as elliptical fitting can characterize possible targets. These approaches should not be considered definitive mine-identification technologies, but rather instruments to prioritize areas and targets for later human assessment and standard mine-action procedures. An integrated algorithmic pipeline is needed to move from magnetic measurements to predictive classification. The workflow includes UAV-based survey planning and systematic data gathering, georeferencing, noise reduction, diurnal correction, gridding, regional-gradient removal, motion-artifact correction, and quality control. The rectified magnetic data are then converted into spatial, spectral, gradient-based, and contextual image representations. These representations can serve as input to supervised models such as SVM, Random Forest, or CNN, or to unsupervised anomaly detection algorithms when labeled data are insufficient. Model outputs could include anomaly

probability maps, target positions, projected item classes, confidence estimates and priority rankings. Qualified mine-action professionals should then verify the outputs before any physical clearance activity.

Building strong models requires a thorough analysis of the size, quality, and diversity of training data. Depending on the architecture and task complexity, deep learning models can require thousands to millions of samples, while traditional techniques can work well with smaller datasets if features are carefully built. But numbers alone are not enough. High-quality labeled data depends on trustworthy ground truth about the location, type, depth, orientation and properties of buried items. Gathering such information is hard—and even dangerous—in polluted or active-conflict areas. Therefore, the training datasets should also include heterogeneity in soil kinds, object categories, burial depth, sensor setup, flight height, terrain characteristics and environmental variables. Synthetic data generation can help alleviate data shortages, especially when high-fidelity digital twins can generate magnetometer signals for UXO and non-UXO items under controlled conditions. However, overreliance on simulated data can create a domain gap between model training and operational deployment; therefore, synthetic data should still be validated against real-world observations. When validating models, avoid overly optimistic performance estimates. Repeated stratified cross-validation allows testing model resilience while preserving class distributions between training and validation groups. K-fold cross-validation repeatedly splits the dataset into training and validation folds. Hold-out testing provides an independent evaluation by reserving some data for final review. Stratified cross-validation is particularly useful when mine and non-mine observations are uneven. It is better to use multiple metrics to assess performance in addition to accuracy. Precision is the ratio of anticipated targets that are truly positive, while recall or sensitivity, is the ratio of true targets that are correctly recognized. F1-score is the balance between precision and recall. Macro F1 gives equal emphasis to each class. The false negative rate is especially important in mine detection, where missing a dangerous object can have serious consequences (Figure 7).

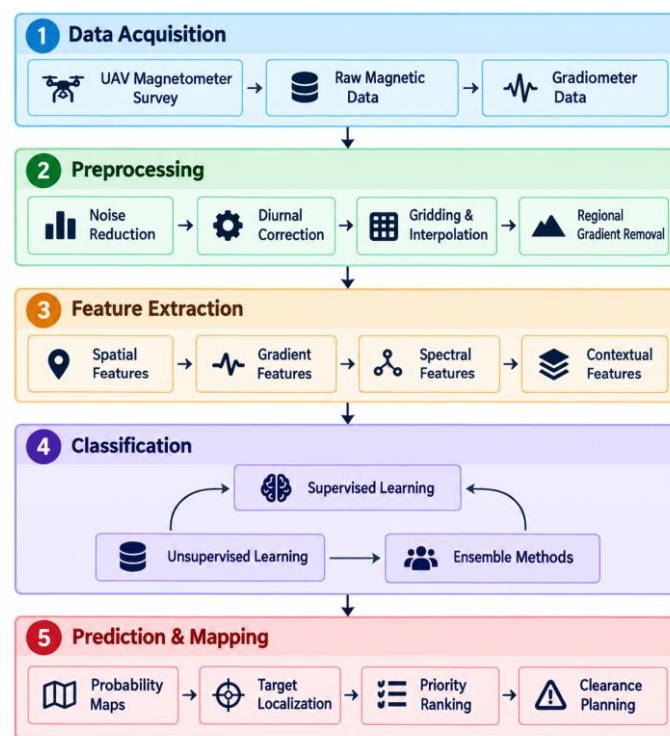


Figure 7: Complete algorithmic pipeline from measurement to prediction

So, model selection should focus on detection reliability and risk reduction, not overall classification accuracy. Deployment factors are operational safety and computational needs. Training the model may require high-performance computing resources; however, inference in the field can run on edge-computing platforms such as Raspberry Pi systems, NVIDIA Jetson devices or other specialized hardware. Edge processing enables local anomaly detection and initial categorization without constant internet connectivity. Connectivity enables cloud infrastructure for centralized data storage, model updates, monitoring, and collaborative analysis. Designing the field system requires consideration of battery consumption, computing capacity, sensor integration, environmental durability and communication reliability. In a safety-critical application, near-zero false-negative performance should be a primary goal, but it is unreasonable to assume any automated system can guarantee zero missed goals. Explainability is also crucial because operators need to understand the reasons behind model predictions, and confidence estimation can help prioritize risks and identify situations for further inquiry. Given the scale of Syria's mine-contamination

situation, these technological advances are especially pertinent. Syria is highly contaminated with landmines and UXO, which has implications for humanitarian access, community safety, agricultural activities, infrastructure rebuilding and economic recovery. In 2025, the Syrian Arab Republic was ranked second in the world for casualties from unexploded ordnance. It was on track to become the country with the most landmine casualties in 2025, according to Landmine Monitor 2025. Landmines and UXO reportedly killed or injured at least 1,612 persons between 8 December 2024 and 3 December 2025. These conditions show that mine and UXO clearance is not an isolated humanitarian action but a prerequisite for wider reconstruction, including debris removal, infrastructure rebuilding, agricultural land rehabilitation and restoration of public amenities. Machine-learning-based magnetic survey analysis should therefore be integrated into existing mine-action procedures, rather than viewed as a substitute for established clearance capabilities. The main goal should be to increase survey efficiency, detect suspicious anomalies, highlight areas for prioritization of inquiry, and support evidence-based decision-making. The overall aim is to shift from a largely reactive clearance strategy to a more predictive, data-driven approach to humanitarian relief. Qualified personnel should integrate machine-learning outputs, such as probability maps, target lists, anomaly classifications, and priority rankings, into existing operational workflows and review them (Figure 8).

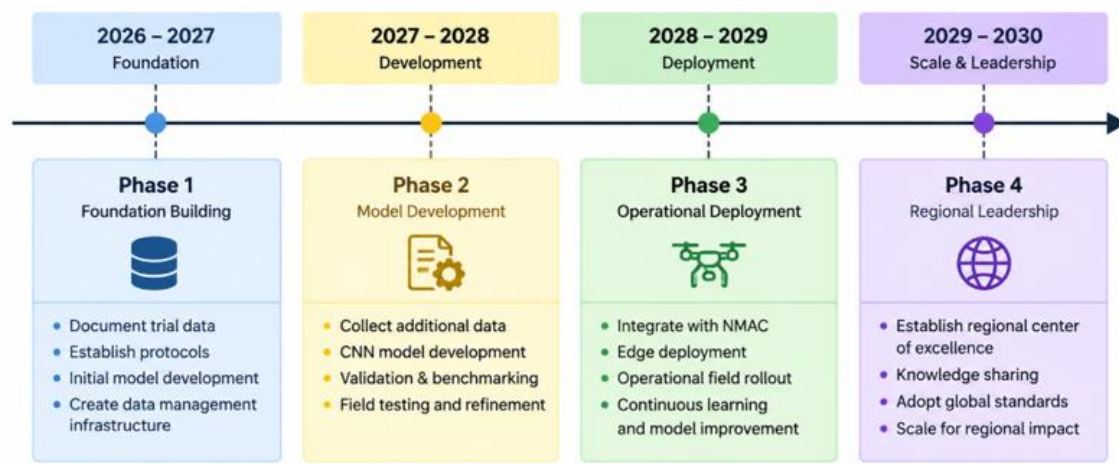


Figure 8: Implementation roadmap for ML-based mine detection in Syria

However, automated models remain susceptible to false positives and false negatives, particularly when applied in environmental conditions that differ from the training data, and human expertise remains crucial. Capacity building is equally vital for long-term success. Fadi al-Saleh said the initiative will succeed in the long run if it secures large numbers of drones and continuously trains staff. This is not just a demand for drone pilots but also for magnetometer operators, data scientists, machine learning engineers, GIS professionals, mine-action experts, and field-validation teams. Systematic data collection and exchange also improve model performance over time. Recent events in Syria have shown the importance of early, targeted monitoring of areas that are not yet cleared. If data collection, labeling, storage, georeferencing, quality control, and secure sharing had established protocols, field data obtained would be added to the model improvement process. Thus, a phased deployment roadmap provides a viable method to operationalize machine learning-based magnetic survey analysis in Syria. During the foundation-building phase (2026-2027), the focus should be on the documentation and analysis of data from the drone trial conducted in November 2025, the development of standardized protocols for data collection, the creation of an initial labeled dataset from existing survey data, and the development of baseline models using machine learning techniques such as SVM and Random Forest.

In the model development and validation phase (2027-2028), the focus should be on collecting additional survey data with reliable ground truth, developing CNN-based classification systems, implementing unsupervised anomaly-detection approaches such as RUDE, testing models on independent datasets, and establishing standardized performance benchmarks. In the operational-deployment phase (2028-2029), verified models could be integrated into relevant mine-action operations, supported by edge-computing infrastructure for field-based inference, continuous model updates and expansion to additional survey regions. Finally, by 2029-2030, Syria could explore developing regional capacity by establishing a center of excellence for machine learning-aided mine action, sharing operational lessons learned with other conflict-affected countries, and contributing to the development of international standards and best practices on the responsible application of machine learning and artificial intelligence for humanitarian mine detection. Such a staged strategy would allow technology development to be combined with data gathering, institutional capacity building, field validation and safety assurance, rather than attempting broad-scale implementation without sufficient proof.

5. Discussions

Using machine learning on magnetic survey data represents a paradigm shift in landmine detection, moving from traditional measurement and human interpretation to automated prediction. In the traditional approach, human experts interpret magnetic anomalies. This makes the process slow, subjective, and reliant on specialized expertise. Machine learning provides automatic, objective and scalable interpretation of raw magnetic readings, transforming them into actionable recommendations. This has major implications for humanitarian demining because automated analysis can process large amounts of survey data far faster than human analysts, enabling rapid examination of large areas. Furthermore, machine learning algorithms can detect subtle patterns in magnetic signatures that manual interpretation may miss, potentially reducing false-negative detections. Once properly trained and validated, these models can be applied across multiple surveys and locations, offering consistent analysis at scale and decreasing human bias and subjectivity. In addition, machine learning can move beyond simple anomaly detection to estimate the probability that a discovered anomaly is a landmine or other unexploded ordnance (UXO), which can aid risk-based decision-making. The reviewed literature has investigated many machine learning and deep learning methods, showing variable performance and applicability for magnetic anomaly detection. Support Vector Machines (SVMs) have recorded a macro-F1 score of about 95.86%, making them successful for limited datasets, and they also offer strong interpretability.

Convolutional Neural Networks (CNNs) have been shown to achieve accuracies above 95.8% and perform automatic feature extraction; however, they often require large amounts of training data. Random Forest algorithms are robust and interpretable for classification, especially with high-dimensional data, and also provide valuable feature-value estimates. When labeled data are unavailable, RUDE, based on One-Class SVM, is an appropriate approach for unsupervised anomaly identification and is beneficial for exploratory applications. Evaluated studies show the strong capabilities of deep learning reconstruction algorithms for magnetic data reconstruction, with reported improvements of roughly 3–5% accuracy and processing speeds up to 80 times faster than conventional methods. Despite these advantages, several problems remain before large-scale field deployment, especially in humanitarian demining applications in Syria. A major difficulty is the absence of labeled training data. This can be addressed through synthetic data production and augmentation, transfer learning from related domains, semi-supervised and unsupervised learning methodologies, and international data-sharing collaborations. Another challenge is computational restrictions, as field-based systems require efficient models that can run on edge devices. Some possible mitigation methods include model compression, quantization, lightweight architectures such as MobileNet, and hybrid cloud-edge computing frameworks.

False-negative detections pose a serious safety risk, as failing to detect a landmine can have grave repercussions. This risk can be mitigated using conservative classification thresholds, human-in-the-loop verification, ensemble learning approaches, and confidence estimates with uncertainty quantification. Environmental variability also influences magnetic signatures because differences in soil composition, moisture, terrain and other local conditions can alter survey measurements. Domain adaptation, context-aware models, and multi-modal sensor fusion can improve model robustness to different environmental situations. International cooperation is also needed to advance machine learning-based mine identification in Syria. Technical support can provide expertise in machine learning, data science, and geophysics, while data-sharing programs can provide access to labeled data from different mine-action environments. Capacity-building projects can train Syrian staff in data collection, magnetic survey analysis, and machine learning approaches. At the same time, technology-transfer initiatives can improve access to sophisticated sensors, processing equipment, and software. Finally, research collaboration among international organizations, academic institutions, humanitarian demining groups and local specialists can promote the cooperative development, validation and implementation of robust machine learning algorithms for safer, more efficient landmine identification.

The investigation provides numerous important insights into the possibilities of applying machine learning-based magnetic survey analysis to the detection of landmines and unexploded ordnance in Syria. This approach is physically based on the magnetic anomalies produced by buried ferromagnetic objects. Magnetic anomalies can be approximated using magnetic dipole models that depend on the object's shape, magnetic characteristics, orientation and burial conditions. These physical relationships underpin computer-based interpretation of magnetic measurements. Magnetic gradiometry is particularly useful because it increases sensitivity to small-scale spatial fluctuations in the magnetic field and improves the identification of localized anomalies associated with buried metallic objects. Thus, combining physically informed survey design with machine learning can improve the efficiency and consistency of anomaly identification while preserving the fundamental principles of magnetic surveying. Performance evaluation indicates that traditional machine learning and deep learning methods have strong potential for categorizing magnetic anomalies. Support Vector Machine classifiers have attained macro-F1 scores of 0.9586 ± 0.0372 in controlled trials. Experiments have also shown that Convolutional Neural Network-based models can classify UXOs with accuracy above 95.8% and an F1-score above 92.5%. Beyond classification, researchers have also used deep learning techniques to reconstruct and interpolate magnetic data. These techniques achieve about 3-5% better reconstruction accuracy and are up to 80 times faster than some state-of-the-art methods. The results indicate that machine learning can benefit multiple points in the detection pipeline: data reconstruction, anomaly recognition, feature extraction, target classification and prioritization. However, performance achieved in controlled laboratory conditions should not be assumed to match performance

in Syrian field contexts, where soil conditions, sensor configurations, background magnetic changes and target distributions may differ considerably.

Feature engineering is another significant predictor of model performance. Selecting, modifying and combining input features can greatly affect standard ML models' ability to distinguish dangerous objects from natural magnetic changes and metallic detritus. Spatial features such as anomaly amplitude, width, shape, gradient and curvature can reveal the physical characteristics of potential targets. At the same time, spectral and gradient-based representations may capture additional patterns not obvious in the raw measurements alone. Incorporating new features like percentile distance has produced demonstrable gains in macro-F1 across several models. This is particularly crucial for Syria, where labeled datasets are projected to be relatively small during the initial implementation phases. Traditional machine learning algorithms can achieve strong performance when trained on carefully selected, physically meaningful features, without the extremely large datasets usually required for deep learning. The Syrian setting demonstrates the operational viability of UAV-based magnetic surveying but also highlights substantial limitations that need to be overcome before it can be scaled up. The November 2025 drone testing showed the operational potential of a UAV-mounted magnetometer system for large-area surveys, with the drone apparently covering about 10,000 square meters in 35 minutes. This coverage may reduce the time and personnel needed for conventional survey methods. It could also support preliminary assessments of areas that are difficult or unsafe for personnel to access. However, GPS instability and poor internet access pose major operational challenges. These constraints may impair positioning accuracy, data synchronization, real-time processing, and communication between field crews and centralized systems. Future systems should therefore integrate accurate georeferencing, local data storage, offline processing capabilities and edge-computing technologies so critical detection functions do not depend entirely on continuous network availability.

Data scarcity is one of the most fundamental challenges in building viable machine learning systems for Syria. Supervised learning requires sufficiently large, representative sets of labeled observations where target locations and properties are known. In contaminated situations, obtaining such ground-truth information is challenging and possibly harmful. Moreover, a dataset from a limited number of places may not represent the diversity of soil, geological, climatic and topographic variables in Syria. Thus, producing synthetic data using high-fidelity digital twins offers a viable way to augment real-world observations. Digital twins can replicate magnetic responses for varied object types, burial depths, orientations, soil conditions, and sensor combinations. However, synthetic data should augment, not replace, field observations, as differences between simulated and real magnetic environments can create a domain gap that degrades model reliability in deployment. The safety-critical nature of mine detection imposes requirements that differ significantly from those of general classification applications. Even if a model is overall accurate, missing a hazardous object even occasionally may make it inadequate. In particular, false negatives are a problem, because an undetected mine or UXO might cause serious harm or death. Thus, model development should aim to minimize false negatives while keeping false positives to an acceptable level. Conservative classification thresholds, uncertainty assessment, anomaly prioritization and human-in-the-loop verification should be integral to the operational system. Treat machine learning forecasts as decision-support outputs rather than autonomous clearance judgments. Properly trained and authorized mine-action personnel must provide final clearance and confirmation. The total integration pathway should be implemented in phases: foundation building, model development and validation, operational deployment and longer-term regional development.

A phased approach like this is better than instantaneous, wide-scale deployment because it lets the technology be tested step by step under increasingly realistic conditions. Each stage provides additional data and operational experience that can be used to improve later stages. The strategy also enables technical standards, safety procedures, staff training and institutional responsibilities to evolve with the machine learning technology. These findings lead to some recommendations to promote the machine learning-based magnetic survey analysis in Syria. The first step is to methodically document and analyze the data produced during the November 2025 drone trial. The analysis should evaluate sensor quality, spatial coverage, positioning accuracy, noise characteristics, the distribution of magnetic anomalies, and operational constraints. This first study would provide an evidence base to determine which technical changes are needed before future data collection.

The second goal is to develop standardized data-collection protocols, including UAV flight parameters, sensor calibration, line spacing, flight altitude, survey speed, positioning, environmental conditions, data formats and quality-control procedures. Standardization matters because inconsistent data collection can reduce the value of observations for training and validating machine learning. The third aim is to build high-quality labeled datasets using current survey data where suitable and, when practical and safe, ground-truth processes. The datasets should include diverse target types, varying burial depths, soil conditions, survey configurations and non-target surroundings. The fourth aim is to create basic baseline models using reasonably data-efficient methods such as SVM and Random Forest. Establishing baseline performance before introducing more computationally expensive CNN architectures will provide a clear standard for comparing subsequent techniques. Do not evaluate the initial models solely on accuracy. Evaluate them based on macro-F1, precision, recall, false-negative rate, and other safety-important metrics. Fifth is controlled validation with defined targets and independent test environments.

Validation should be conducted under conditions that simulate the variability expected during operational surveys, including variability in soil properties, target depth, target orientation, sensor altitude, and environmental background. Such testing is needed to assess whether reported performance in laboratory or controlled field conditions generalizes to real Syrian situations. The sixth priority is to strengthen Syrian personnel's technical capacity. Sustainable deployment cannot rely on external professionals alone; it will require training local staff in magnetic surveying, UAV operation, GIS, data administration, machine learning, model evaluation, cybersecurity, and field validation. Developing this capacity would also enable continuous improvement as fresh survey data become available. Finally, the paper should develop international relationships with appropriate research institutes, humanitarian mine-action bodies, technology suppliers, universities and specialized laboratories. Partnerships can provide access to technical experience, training resources, equipment, research collaboration, validation facilities and worldwide best practices. But relationships should be based on long-term capacity transfer, not perpetual reliance on external support. The final objective should be to build sustainable Syrian capability so local institutions can collect and maintain survey data, train and test machine learning models, operate UAV-based survey systems, and incorporate analytical outputs into existing mine-action protocols. Overall, the results suggest that machine learning analysis of magnetic surveys is a promising technology for Syria's mine-action and reconstruction efforts. Still, its value will depend on data quality, operational validation, institutional capacity, and compliance with safety requirements. This implies that the technology should be developed as a human-supervised decision-support system, not a fully autonomous mine-detection or clearance device. The most feasible strategy for reliable, scalable implementation is a systematic progression from trial-data analysis and standardized data collection to baseline modeling, controlled validation, field deployment and capacity building.

5.1. Recommendations

Building a national data infrastructure for mine action and magnetic survey analysis should be one of the Syrian Government's highest priorities. The Syrian Government should create standardized processes for collecting, processing, storing, georeferencing and managing magnetic survey data from UAVs and other geophysical equipment. A centralized database could be an organized repository of magnetic measurements, survey sites, target classifications, environmental conditions, processing outcomes and ground-truth information. Such infrastructure would integrate data across multiple areas and institutions into a coherent national framework, providing a vital basis for developing and validating standardized machine learning models. The system should also develop data quality requirements and metadata standards to ensure datasets remain available for future research. Where necessary and compatible with security and humanitarian requirements, channels should be devised to share data with international partners, research institutes and mine-action organizations on a controlled basis. Mine-action data may contain sensitive information on contaminated sites and operating activities, so the national data infrastructure should include access protocols, security precautions, backup protocols and data-governance procedures. The Syrian Government should also build technical capacity, as the long-term sustainability of machine learning-based mine detection cannot rely solely on foreign technical professionals. Personnel involved in mine action should be trained in magnetic data acquisition, UAV operation, preprocessing, geospatial analysis, machine learning, model evaluation and interpreting anomaly maps. Partnering with Syrian universities and academic institutions can help develop specialized training programs and research opportunities. Introducing certification or competency-based training programs for staff working with machine learning technologies in mine action could help ensure operators understand the technological capabilities and limitations of automated systems. International professionals can help through structured knowledge-transfer programs, workshops, fellowships, joint research, and practical field training.

The goal should be to establish a domestic technical workforce that maintains data systems, evaluates algorithms, troubleshoots field equipment and continuously improves analytical models. Another key area for government funding is research and development. Pilot projects should be funded to assess machine learning-based magnetic detection in Syria's varied climatic and operational settings. Through worldwide partnerships with universities, research institutes, humanitarian groups and technology companies, Syria can access specific skills in geophysics, artificial intelligence, UAV systems, sensor technology and data science. A national research program in mine-action technology might provide a formal process for evaluating new technologies, such as supervised machine learning, deep learning, unsupervised anomaly detection, synthetic data, digital twins, and edge computing. Research results and operational lessons learned need to be consistently documented to provide future studies with effective techniques, technological constraints and implementation issues. Importantly, research funding should prioritize field validation over laboratory demonstrations or benchmark datasets alone. Finally, integrate machine learning into national mine-action protocols, supported by appropriate operational and regulatory structures. Standard operating procedures should describe how machine learning outputs are generated, understood, checked, documented, and used in survey and clearance decisions. Develop quality assurance and quality control mechanisms to evaluate sensor performance, data quality, model dependability and field findings. Rigorously validate models with independent datasets and controlled test conditions before deployment. Procedures should also define acceptable error rates, uncertainty levels, escalation paths, and scenarios under which human experts must override computerized predictions. Machine learning should support decisions, not replace them. Its results should be compatible with existing mine-action processes such as non-technical survey, technical survey, target investigation, clearance, quality control and post-clearance documentation. International partners play a vital complementary

role in helping Syria build machine-learning-assisted mine-action capabilities. Technical help could include experience in machine learning, magnetic geophysics, UAV-based surveys, GIS, data engineering, cybersecurity and model validation.

International organizations and technology vendors can help build national data infrastructure and help develop interoperable data formats and standards. Training and capacity-building activities should address not only academic knowledge but also practical execution, including field surveying, sensor calibration, data preprocessing, anomaly interpretation and model evaluation. Technology transfer should be planned to enable Syrian institutions to operate and sustain systems independently after the initial phase of external support. International partners can also play an important role in data collection and data sharing. Training baseline models could benefit from access to properly documented, ethically shareable labeled information from other mine-affected ecosystems. However, foreign datasets should not be copied or assumed to reflect Syrian conditions. Variations in soil characteristics, target types, survey instrumentation, geography and environmental conditions can all influence magnetic signals. International help should include approaches for domain adaptation, dataset harmonization and validation utilizing Syrian field data. Partners can also build systems for synthetic-data creation and digital twins that simulate realistic magnetic responses under various environmental and target conditions. Shared data platforms and common standards could further strengthen collaboration between Syrian institutions and international organizations while ensuring strong security and privacy safeguards. International aid should also concentrate on funding research and development. Donors and research groups can fund pilot deployments, algorithm development programs, controlled validation studies and the creation of systems that could be deployed in the field. Funding strategies should incentivize partnership work between Syrian institutions and international technical partners rather than isolated projects with minimal long-term benefit. Technologies that can operate under infrastructure constraints, such as local data processing and edge-based inference without dependable internet connectivity, should receive particular consideration.

Funding should cover not only the initial equipment purchase, but also maintenance, staff training, equipment replacement, data administration, and long-term evaluation. International coordination is important to avoid fragmented aid that can result in duplication of effort, incompatible systems and ineffective use of resources. International partners should coordinate through an appropriate institutional mechanism to support national-level Syrian mine-action priorities. Common technical standards, agreed goals, compatible data sets, and clear duties can increase complementarity across participating entities. Coordination should also help ensure that technology-driven initiatives align with operational mine-action needs rather than evolving independently of field realities. A specialized coordination mechanism could enhance communication between government entities, humanitarian organizations, research institutions, donors, technology providers and international mine-action specialists. Humanitarian organizations should use machine learning in mine-action operations only if evidence shows it will increase survey efficiency, anomaly prioritization or operational decision-making. Rather than viewing machine learning as a substitute for traditional mine-action techniques, organizations should use it as an added layer of analysis within existing survey and clearance processes. Well-documented surveys can contribute to future model development and validation. Resources should support systematic data gathering. Organizations should also document operational experiences, including successful uses, false positives, false negatives, environmental limitations and technical failures and share lessons learned through appropriate professional and humanitarian channels. This information is needed to determine where machine learning offers real operational benefits and where more traditional methods remain more appropriate. Humanitarian groups need to focus on building local capacity. Training local people in UAV operation, magnetic surveying, data administration, GIS, machine learning and field validation can reduce reliance on external experts and improve the sustainability of mine-action initiatives.

Local-level partnerships with universities, technical institutes, community organizations and relevant government authorities can help create a wider ecosystem for skills development and technology uptake. "Technology and skills should be shared through actual training and coordinated application, not by contributions of equipment. Providing modern equipment without developing the personnel to operate, maintain and evaluate it would create an unsustainable dependency. Finally, humanitarian organizations must continue to advocate for investment in breakthrough mine detection systems, but with realistic expectations of their capabilities. Machine learning-aided magnetic surveying has strong potential, but one should be cautious about claims of near-flawless autonomous identification, as performance can degrade when models are used in environmental variables or target configurations not present in the training data. This calls for further research, field validation, independent assessment and transparent reporting. Syria's expertise in UAV-based magnetic surveying and machine learning could help build an international evidence base over time, recording not just successful applications but also operational issues. Syria could share lessons learned with other conflict-affected and post-conflict nations grappling with comparable contamination challenges, potentially leading to better international procedures and standards for responsible AI-assisted mine action. Ultimately, effective implementation will require coordinated action, not separate technological investment. The Syrian Government should provide institutional leadership, data governance, regulatory structures, and national capacity. International partners should provide technical expertise, funding, research collaboration and technology transfer. Humanitarian organizations should translate validated technologies into operational practice while developing local capabilities. This division of responsibility may foster an environment where machine learning supports, rather than undermines, established mine-action norms. But the core focus must remain on humanitarian safety: improving the identification and prioritization of hazardous areas, ensuring

each automated prediction is properly validated, and ensuring technological innovation feeds directly into safer, more efficient clearance operations.

6. Conclusion

Syria's landmine contamination crisis—with over 15.4 million people at immediate risk and the country on course to record the highest number of landmine casualties globally in 2025—demands innovative solutions. Traditional manual demining methods, while effective, are too slow and too dangerous to address the scale of the challenge. Applying machine learning to magnetic survey data offers a transformative pathway from measurement to prediction, enabling faster, safer, and more effective humanitarian demining. The physical foundations are well understood: buried ferromagnetic objects create detectable magnetic anomalies that can be modeled as magnetic dipoles. Magnetic gradiometry, particularly when deployed on UAV platforms, provides the sensitivity and coverage needed for large-scale surveys. Syria's November 2025 drone trial demonstrated the approach's operational feasibility, with the Setera drone scanning 10,000 square meters in just 35 minutes. The algorithmic landscape is rich and rapidly evolving. SVM classifiers have achieved macro-F1 scores of 0.9586 ± 0.0372 in controlled trials. CNN-based models have demonstrated UXO classification accuracies exceeding 95.8%. Deep learning approaches for magnetic data reconstruction have achieved 3–5% higher accuracy while operating up to 80× faster than state-of-the-art algorithms. Unsupervised methods such as RUDE offer viable alternatives when labeled training data is limited. Yet significant challenges remain. Data scarcity—limited labeled training data—remains a critical constraint.

The safety-critical nature of mine detection demands near-zero false negative rates, requiring conservative classification thresholds and human-in-the-loop verification. Field-deployable systems impose computational constraints that require efficient edge-computing models. Diverse environmental conditions across Syria's fourteen governorates create variability that domain adaptation and context-aware modeling must address. The path forward requires coordinated action across multiple dimensions. A phased implementation roadmap—foundation building, model development, operational deployment, and regional leadership—provides a framework for systematic progress. International cooperation is essential for technical assistance, data sharing, capacity building, and technology transfer. As one analysis observed, "by shifting the paradigm from reactive clearance to predictive, data-informed humanitarian response, the system enhances the safety and sustainability of land release operations." Developing machine learning algorithms to analyze magnetic survey data—from measurement to prediction—marks a critical step toward this paradigm shift. The decisions made in the coming years will determine whether Syria can leverage this transformative technology to accelerate the clearance of landmines and explosive remnants of war, enabling the return of displaced populations, the rehabilitation of agricultural land, and the reconstruction of communities devastated by nearly 15 years of conflict.

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References

1. L. S. Yoo, D. Jung, and Y. Choi, "Metallic landmine detection and identification using machine learning classification of UAV-based magnetometer data," *Taylor & Francis*, vol. 40, no. 15, pp. 2845–2873, 2026.
2. C. Yilmaz, H. T. Kahraman, and S. Soyler, "Passive mine detection and classification method based on hybrid model," *IEEE Access*, vol. 6, no. 8, pp. 47870–47888, 2018.
3. V. Lytvyn, I. Peleshchak, V. Vysotska, V. Motyka, and R. Peleshchak, "A passive approach to mine detection and classification utilizing magnetic fields and convolutional neural networks," in *proc. IEEE 17th International Conference on Advanced Trends in Radioelectronics, Telecommunications and Computer Engineering (TCSET)*, Lviv, Ukraine, 2024.

4. R. M. Peleshchak, V. V. Lytvyn, M. A. Nazarkevych, I. R. Peleshchak, and H. Y. Nazarkevych, "Influence of the symmetry neural network morphology on the mine detection metric," *symmetry*, vol. 16, no. 4, pp. 1–14, 2024.
5. H. P. Myers, "Safer grounds: A study of landmine detection using UAV- and ground-based multi-modal geophysics," Ph.D. dissertation, *University of Maryland*, Maryland, United States of America, 2024.
6. W. Deleersnyder, J. Lopez-Alvis, L. Beran, and L. Heagy, "Discriminating dipole signals from geologically noisy electromagnetic induction data with convolutional neural networks," in *Proc. EGU General Assembly 2026*, Vienna, Austria, 2026.
7. L. Heagy, J. Lopez-Alvis, D. Oldenburg, L. P. Song, and S. Billings, "Using convolutional neural networks to classify unexploded ordnance from multicomponent electromagnetic induction data," in *Proc. EGU General Assembly 2025*, Vienna, Austria, 2025.
8. Z. Wen, S. Han, C. Gao, Y. Chen, L. Guo, and Y. Zhang, "A deep learning method for recognizing types of unexploded ordnance based on magnetic detection," *IEEE Trans. Geosci. Remote Sens.*, vol. 62, no. 5, pp. 1–13, 2024.
9. K. Kuru, D. Ansell, D. Jones, B. Watkinson, J. M. Pinder, R. Hamila, and C. Tinker-Mill, "Automated airborne ordnance detection using data fusion of magnetometer and ground penetrating radar," in *Proc. Interdisciplinary Conference on Electrics and Computer (INTCEC)*, Chicago, Illinois, United States of America, 2025.
10. M. Kovalenko, D. Przewozny, P. Chojcecki, A. Hilsmann, P. Eisert, and S. Bosse, "AI-based denoising and interpolation of magnetic UXO data," in *Proc. IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Vienna, Austria, 2025.
11. R. Peleshchak, V. Lytvyn, I. Peleshchak, and S. Voloshyn, "Neural network technology of mine recognition based on data from magnetic field sensors," in *Proc. IEEE 12th International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS)*, Dortmund, Germany, 2023.
12. S. Gürkan, M. Karapinar, and S. Dogan, "Classification of explosives materials detected by magnetic anomaly method," in *Proc. 2017 4th Int. Conf. Elect. Electron. Eng. (ICEEE)*, Ankara, Turkey, 2017.
13. X. Zheng, Y. Tian, and B. Wang, "A magnetic gradient tensor-based method for UXO detection on movable platform," *IEEE Trans. Geosci. Remote Sens.*, vol. 61, no. 3, pp. 1–9, 2023.
14. P. Ściegienia and M. Blachnik, "On the development of a neural network architecture for magnetometer-based UXO classification," *Appl. Sci.*, vol. 15, no. 15, pp. 1–10, 2025.
15. Syrian Arab News Agency (SANA), "Emergency Ministry conducts first practical trial using drone for landmine detection," *SANA*, 2025. [Accessed by 10/06/2026].
16. Welat TV, "Germany supplies Syria with drones for landmine detection," *Welat TV*, 2025. [Accessed by 11/01/2026].
17. 963 Media, "German drone tested in Syria: New step in mine-clearance efforts," *963 Media*, 2025. [Accessed by 06/01/2026].
18. R. Alabi, "Syria conducts first practical drone experiment for mine detection," *The Media Line*, 2025. [Accessed by 12/01/2026].
19. K. Kuru, "Magnetic field mapping of a landmine field using a magnetometer-integrated drone and intelligent application," *IEEE Dataport*, 2024. [Accessed by 15/05/2025].
20. L. S. Yoo, J. H. Lee, Y. K. Lee, S. K. Jung, and Y. Choi, "Open Access Communication Application of a Drone Magnetometer System to Military Mine Detection in the Demilitarized Zone," *Sensors*, vol. 21, no. 9, pp. 1–15, 2021.
21. A. P. Hoffmann, M. G. Finley, E. Zesta, M. B. Moldwin, and L. V. Ojeda, "A drone-mounted magnetometer system for automatic interference removal and landmine detection," *arXiv arXiv:2510.01417*, 2025. [Accessed by 18/06/2026].
22. Mines Advisory Group (MAG), "Syria landmine emergency: MAG scales up response," *Mines Advisory Group*, 2026. [Accessed by 22/06/2026].
23. Enab Baladi, "Syria tops list of countries most affected by landmines," *Enab Baladi*, 2025. [Accessed by 25/01/2026].
24. A. Barnawi, K. Kumar, N. Kumar, B. Alzahrani, and A. Almansour, "A deep learning approach for landmines detection based on airborne magnetometry imaging and edge computing," *Computer Modeling in Engineering & Sciences*, vol. 139, no. 2, pp. 2117–2137, 2024.
25. M. A. J. Orman-Kollmar, "Ultralight Electromagnetic Systems on Moving Platforms with Advanced Signal Processing for Subsurface Target Detection, Localization, and Identification," Ph.D. dissertation, *Dartmouth College*, Hanover, New Hampshire, United States of America, 2026.

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