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REVIEW

A comprehensive review on landmine detection using deep learning techniques in 5G environment: open issues and challenges

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Abstract

Detection of Landmines, especially anti-tank mines, bombs, and unexploded substances, is one of the major challenges facing humanity. The devastation and human tragedy associated with undetected explosives are self-evident in war-torn communities. To deal with this problem, we are only left with proactive measures that such substances must be detected and dealt with before the fallout. Most available solutions have major shortcomings, such as cost, efficiency, and accuracy, where the trade-offs among them are inversely related. On the other hand, advances in deep learning, unmanned aerial vehicle, and sensing are making their way as potential technologies to revolutionize the detection and removal of landmines. In this paper, we go through the literature reviewing the most recent work featuring computerized technologies to detect landmines. To our knowledge, no such study has taken place in this respect. Our aim is to find out how deep learning can be integrated with landmine detection. We identify open challenges toward viable automated solutions that enable deep learning to optimize performance effectively.

Keywords Landmine · Deep learning · Applied artificial intelligence · Magnetometery · Ground penetrating radar · Hyperspectral imaging · UAV

1 Introduction

The landmine is an explosive device buried underground to demolish or disable enemy targets, whether soldiers, vehicles, or tanks, as they travel through or close to it. Detonation is usually caused by pressure applied by a target walking or driving on the device; however, alternative detonation methods are also employed [1, 2]. A landmine can inflict damage by the direct blast, splashing pieces, or both.

Landmines are problematic as they have an indiscriminate potential as weapons. Many years after a battle ends, they can be harmful and cause damage to the economy and civic society. According to the report of the United Nations [3], 78 countries are contaminated by landmines, with 15,000–20,000 casualties each year. Also, the International Campaign to Ban Landmines recorded over 1,30,000 casualties from mines, improvised explosive devices (IEDs), and explosive remnants of war (ERW) in 120 countries from 1999 to the end of 2019 [4]. In 2019, 78% of all casualties involved civilians (42% by children), 20%

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military and security personnel, and 2% deminers [5]. To overcome these issues, academics and industrial researchers designed and developed landmine removal techniques.

In many countries around the world, landmine removal is a major problem. The various challenges involved in removing landmines are: (i) missing information on the types of landmines used (ii) the areas where they were located initially. (iii) shift in position of landmines due to environmental and physical factors (iv) widespread heterogeneity of anti-tank (AT) and anti-personnel (AP) types of landmines (v) high location and removal costs (vi) sensitivity to explosion with time. Various techniques such as metal detection, ground-penetrating radar (GPR), thermal infrared imaging, multispectral and hyperspectral imaging, fluxgate sensor array, etc., are designed and studied to address these problems.

The aforementioned techniques are suitable for detection based on the kind of mining case, the explosives used, and the ground under certain conditions. In general, most landmines have three major units: a sensor to detect the landmine signature, a signal or data processing unit to organize the sensed input in a detective manner, and a decision-making unit to determine the presence of the landmine. Despite this, each of the techniques mentioned above suffers from some disadvantages such as clutter, false alarms, trouble detecting deep objects, unsuitable for detecting plastic ones, blocked by camouflage or foliage, do not work well when there is vegetation, and insufficient sensitivity. To solve these problems, researchers integrated deep learning techniques.

Deep learning is a subset of machine learning formulated on artificial neural networks with representation learning (supervised, semi-supervised, or unsupervised). To identify and detect landmines, deep neural networks, deep belief net- works, graph neural networks, recurrent neural networks, and convolutional neural networks were employed, resulting in equivalent results, which in some cases exceeded detection techniques' effectiveness. The integration of deep learning with landmine detection provides the following advantages:

(i) improves the detection probability, (ii) reduces the false alarms and clutter, (iii) facilitates precise target localization, deals with small image patches with high accuracy, and extract features effectively to learn real-time data.

The use of deep learning in landmine detection aims to localize and detect different landmine signatures in the sensed data of the minefield. It can help leverage the advantages of deep learning to automate the task of landmine detection. The job resembles the object detection problem where the target objects are the landmines. It involves the analysis and processing of the captured data using different models. The inspection of the target region using various sensing technologies generates the input data. The captured data is further examined to obtain the distinguishing features of landmines. In multiple cases, these features are challenging to identify from the captured data. The presence of clutter in the region further makes the task more difficult. The deep learning models involve automatic feature extraction and learning using the input data. It can thus help to automate the detection process by automatically learning the essential features that can be used to detect the landmine locations. Also, considering different sensing technologies that gather various types of information, deep learning can be pretty helpful in detecting the mine.

The identification of landmines can also be made in the form of instance segmentation. It involves pixel-level identification of the landmine signatures in the sensed data [6]. In object detection, the output is in the form of bounding boxes that contain the object. But segmentation involves detailed segregation of the complete entity from the background. It includes semantic and instance segmentation. The semantic segmentation considers different instances of the same category as a single unit, while instance segmentation treats each instance separately. Multiple landmines can be deployed in a minefield or target region. So the instance segmentation can help segregate each landmine signature in the sensed data.

The input data for the deep learning models for landmine detection contain sensor readings for the target region. The landmine contains certain components like casing, explosive material, etc., that exhibit some physical characteristics that are different from the surrounding environment. It formulates the signatures of the landmines that can be monitored using various sensing technologies. In landmine detection, the target is to detect these signatures or anomalies present in the sensed data that can give the locations of landmines in the target region. The deep learning models automate this task by extracting the features and then learning from the extracted features. The extent of the anomaly decides the boundary of the detected landmine signature in the data. The target region often contains clutter that hampers the detection of landmine signatures. So careful processing of the gathered data is required to remove the effect of clutter. For instance, Fernández et al. [7] have used time gating and average subtraction techniques for removing the clutter effect in data collected using Ground Penetration Radar (GPR). The pre-processing of sensed data can reduce the clutter effect, improving the quality of input data for the deep learning models.

Landmine detection remains a challenging task, despite the popularity of deep learning models for object detection and segmentation. There is not a standard sensing technology that can be used to identify landmines. So the input data for the detection model differs according to the sensors used. Data quality and size are also crucial to the success of deep learning models. However, limited data samples in landmine detection can be used to train and test the model. In addition, the distribution of the training and testing data should be similar to get better results. The models used for the detection task are often very deep, requiring sufficient resources and time to produce the final output. Lastly, the landmines have shape, size, and build materials that can be deployed in a cluttered environment, making the detection difficult.

In recent times, unmanned aerial vehicles (UAVs) have been used to carry out aerial surveys. The research community has studied the same for landmine detection, where UAVs equipped with required sensors traverse the target region [8]. It can reduce the risk and time involved with the region survey. The UAV undertaking the aerial survey communicates with the nearby base station that controls the overall operation. The recent advances in communication technology like 5G and applications like the Internet of Things (IoT) play a crucial part in aerial communication involving UAVs. Depending upon the application and operating region, UAVs have also been used for enhancing coverage and capacity of beyond 5G wireless communication [9]. In such cases, UAVs also serve the role of intermediate nodes or flying base stations. It helps to carry out the operation in remote locations that are not easily accessible. Further, the integration of fog computing with the UAVs enhances their role by providing them with additional computing capabilities [10]. Certain challenges exist in the aerial communication system working with these technologies for landmine detection. As with any wireless technology, the most critical aspect is secure communication. Then UAVs have limited resources, so the communication and processing costs should be minimal.

1.1 Scope of this survey

In this subsection, the exiting surveys by various authors on different Landmine-detection approaches [11, 12] are described in detail. The majority of these surveys centered on a single strategy for detecting and identifying landmines. But to our best insight, no exhaustive study has examined how deep learning can be integrated with landmine detection approaches. The suggested survey included the effects of deep learning on landmine detection. The description of existing surveys is summarized as follows.

Suganthi et al. [11] suggested a hierarchical method based on infrared images that would identify landmines using pre-processing, segmentation, feature extraction, and an ANN-based classification. Yuksel et al. [13] suggested a model of the Markov multi-instance hidden to classify time series data and was created using stochastic expectation maximization to construct its training. Unlike [13, 14] authors studied simultaneous context learning and sequence data classification. The authors have also created a mix of experts from the Markov hidden model to solve the difficulties in constructing classifica tions with various subclasses that rely on their context. Makki et al. [15] have used hyperspectral imaging techniques and image processing tools at different light spectrum wavelengths to detect the landmines and buried objects. Bestagini et al. [16]. introduced the strategy for landmine detection by considering multi-polarization GPR acquisitions. Silva et al. [17]. used multispectral images to detect the landmines. The authors have used classifier fusion and deep learning techniques to achieve the target. The UAV-based underground SAR imaging system has been introduced in [7] for detecting buried items. The main purpose was to detect explosives, such as anti-personnel landmines, but it can also be utilized when it was required to detect and identify concealed items (Table 1).

Gurkan et al. [18] were passively examined the detection and classification of underground objects as non-explosives or explosives. The authors used the fluxgate sensor array to detect the passive magnetic field and the nearest neighborhood method to categorize the resultant data. Rafique et al [19]. used the historical demining data and machines learning technique to estimate the risk of landmine contamination. In contrast to [19], authors in [20] investigated the methods based on deep learning and ground-penetrating radar (GPR) for civil engineering examination. Baur et al. [21] signified the prospects of time-lapse thermal-imaging technology to identify unique thermal signatures corresponding to plastic munitions and explosives of concern (MECs). The efforts at machine learning to make decisions in the demining process were explored by [22]. Priya et al. [23] introduced the usage of region convolution neural network (RCNN) in thermal imaging to identify the subsurface objects and landmines. Travasoos et al. investigated the application of artificial neural networks and machine learning in data interpretation of GPR. Yoo et al. proposed a UAV-based magnetometry system and a data- processing strategy for the detection of metallic landmines in the demilitarized zone. The methodology of modeling and simulating explosive target positioning in terrain spectral images were provided by [12], taking into consideration unexploded ordnances, land mines, and improvised explosive devices. Girschik et al. [24]. proposed detection algorithm to detect the landmines. Here, the authors proposed two approaches. In the first approach, the high-capacity CNN is used to localize and segment the objects. Secondly, supervised pre-training was used for the auxiliary task.

Table 1 Comparison of the proposed and existing state-of-art landmine detection surveys

Year	Author	GPR	UAV/drone	Therml image processing	Magnetometer	Markov models	Metal detector	Multispectral images	Hyperspectral images	Infrared images
2014	Suganthi et al. [11]	×	×	×	×	×	×	×	×	✔
2015	Yuksel et al. [13]	×	×	×	×	✔	×	×	×	×
2016	Yuksel et al. [14]	×	×	×	×	✔	×	×	×	×
2017	Makki et al. [15]	×	×	×	×	×	×	×	✔	×
2018	Fernández et al. [7]	✔	✔	×	×	×	×	×	×	×
	Bestagini et al. [16]	✔	×	×	×	×	×	×	×	×
2019	Silva et al. [17]	×	×	×	×	×	×	✔	×	×
	Gürkan et al. [18]	×	×	×	✔	×	×	×	×	×
	Rafique et al. [19]	×	×	×	✔	×	×	×	×	×
2020	Tong et al. [20]	✔	×	×	×	×	×	×	×	×
	Baur et al. [21].	×	✔	×	×	×	×	×	×	×
	Safatly et al. [22]	×	×	×	×	×	✔	×	×	×
2021	Priya et al. [23]	×	×	✔	×	×	×	×	×	×
	Travassos et al. [102].	✔	×	×	×	×	×	×	×	×
	Yoo et al. [103].	×	✔	×	×	×	×	×	×	×
	Bajic et al. [12]	×	✔	×	×	×	×	×	✔	×
-	Proposed survey	✔	✔	✔	✔	✔	✔	✔	✔	✔

1.2 Motivation and contributions

It is observed that the autonomous detection of landmines is a vital area of research. Researchers integrate different methods to enhance the mine detection rates and reduce false alarms. During the region survey, the detection is affected by surrounding environmental conditions like the changing sunlight, weather conditions, and soil humidity. This paper studies the impact of deep learning techniques in detecting landmines and buried objects. The following are the major contributions of the paper:

- Describe the history, classification, and demining con cepts of landmines.
- Discuss the different types of landmine detection tech niques.
- Analyze the impact of integrating deep learning tech niques in detecting of landmines and buried objects.

1.3 Organization and roadmap

The composition of the paper is conveyed in Fig. 1, and its organization is given as follows. Section 2 presents the history, classification, and demining concepts related to landmines. In Sect. 3, the techniques of landmine detection are explored in detail. A discussion of the impact of integrating deep learning into landmine detection is provided in Sect. 4. Section 5 presents the open issues and challenges associated with landmine detection. Section 6 concludes the paper with some future directions.

Figure 2 gives the roadmap of the paper. Readers interested in understanding the basics of landmine detection can emphasize Sects. 1, 2, and 6. Sections 3 and 4 describe landmine detection techniques and deep learning techniques. Lastly, Sects. 1, 3, 4, and 5 are suggested for the readers intended to gain a high-level overview of landmines, including open research issues and challenges.

2 History, classification and demining

2.1 History

The basic idea behind the mine was established in the course of military history. Zhuge Liang from the Kingdom of Shu, China, established the kind of landmines in the third century. Forces sometimes excavated tiny, small, and large holes in ancient Rome to cover and armed with a

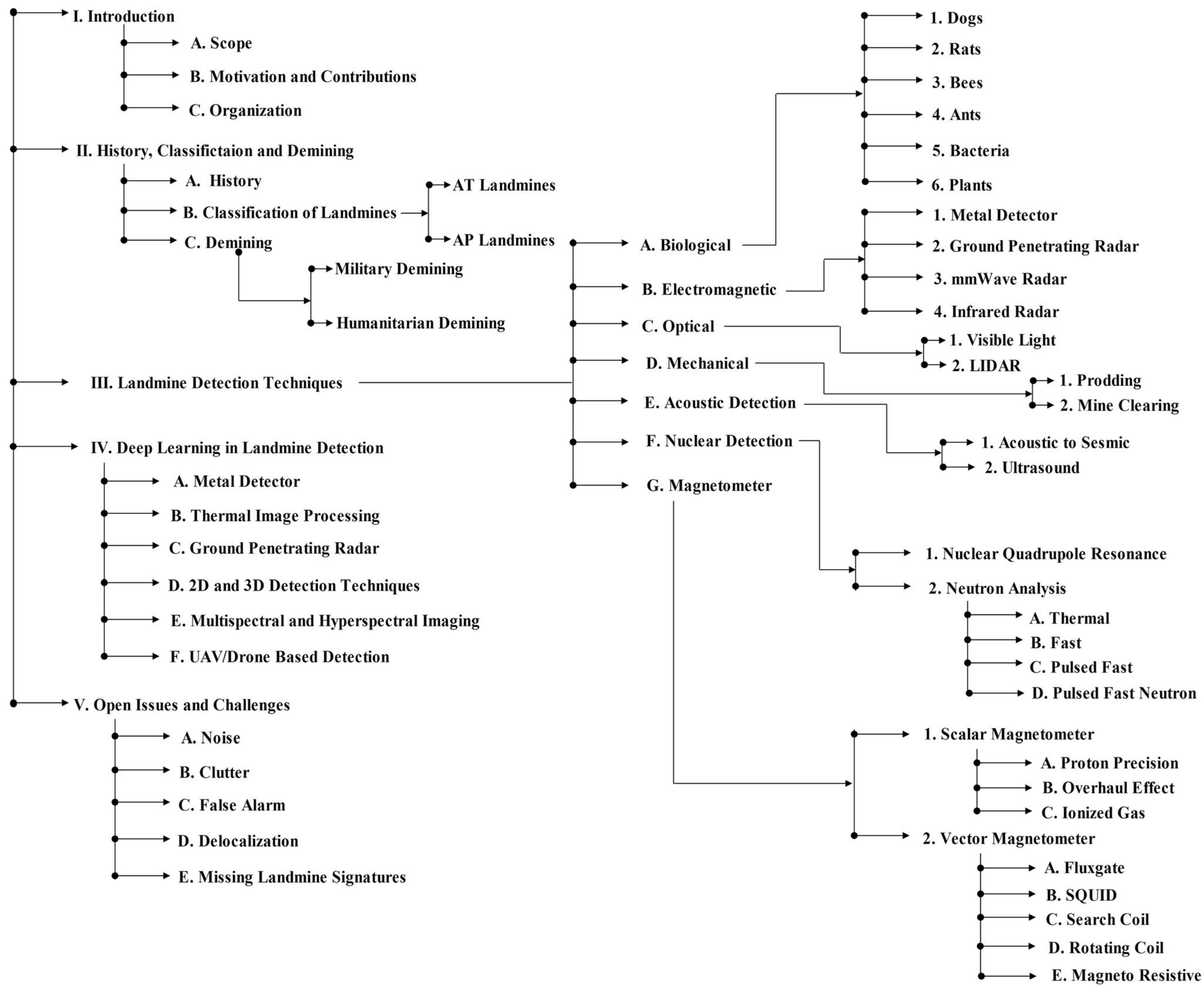

Fig. 1 Organization of the paper

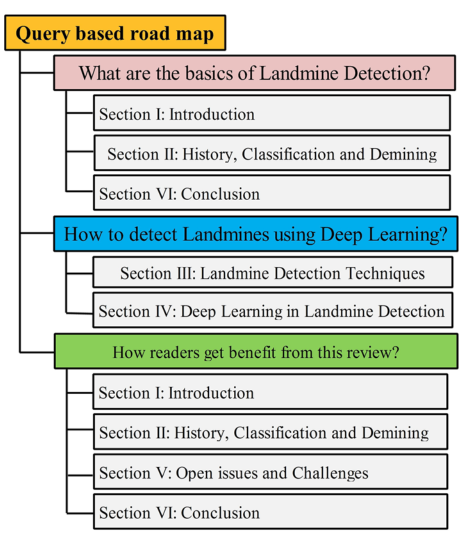

Fig. 2 Roadmap of the paper

sharp spike. During the middle ages in Europe, a small, four-pronged spike weapon, known as caltrops, or crow's feet, may postpone the enemy's march. Around the 14th or fifteenth century [25], the Ming Dynasty began building numerous modern major powder-shaped mines of steel, earthenware, or pig iron.

The first sophisticated mechanical-fused high-exploding anti-personnel mining operations were built during the 1862.

assault of Yorktown by Brigadier General Gabriel J. Raines. During the Wars of the Seminole [25], Raines employed explosive booby traps as a Captain in Floride. The "land tor- pedos" are employed mechanically and electrically, although generally, mechanical fumigation is more dependable near the end of the battle. Many of these designs were altered on the floor; around 2,000 conventional "Raines" mines, particularly from explosive cabinets, were used toward the war's end.

In Imperial Germany, better mining designs were created about 1912, and they were replicated and built by all the main actors during the First World War. Landmines, particularly in World War-I, were used at the start of the Passchendale battle. The British had manufactured landmines with poison gas rather than explosives long before the war was over. At least in the 1980s, the Soviet Union manufactured poison gas mines. At least in the 1950s, the USA was familiar with this concept [25].

2.2 Classification of landmine

There are three components for each mine: casing made of metal, wood, plastic or mixed materials, an explosive substance which may be trinitrotoluene (TNT), royal demolition explosive (RDX), combined RDX/TNT, tetryl or other explosives, and an initiator with the pressure sensor, electronic sensor or other sensors. The differentiation of landmines is based on their design and target, whose description is given as follows.

1) *According to design* Landmines may be divided into two major kinds depending on their design: blast and frag- mentation.
    a) *Blast landmines* These are buried near the surface of the earth and are usually triggered by pressure or manipulation and perturbation. Pressure-enabled landmines require generally about five to sixteen kilograms of pressure. These mines have the principal objective of destroying a nearby target. The blast is meant to fraction the item in question, which can cause secondary harm, including infection and amputation.
    b) *Fragmentation landmines* These mines either release fragments in multiple directions or can be organized in one direction to forward fragments. It may injure and kill up to a distance of 200 m. The pieces of these mines are metal or glass.
2) *According to target* There are two basic categories of landmines based on the intended target: Antipersonnel (AP) landmines and Antitank (AT) landmines. The description of these two kinds is as follows.
    a) *AT landmines* AT mines are generally hidden on highways and rails and are designed to explode by heavy-duty vehicles. A person with an electric wire can trigger them. It is meant to damage tanks or vehicles.
    b) *AP landmines* These tiny explosives detonate or are upset when they are trodden on. Their principal military objective is to mutilate and not kill opposing soldiers.

2.3 Demining concepts

Demining is the procedure through which buried landmines are detected and removed. Two different forms of demining are military demining and humanitarian demining.

a) *Military demining* The objective of military demining is to identify and remove adequate landmines so that soldiers and/or vehicles may travel in secure corridors. The military may tolerate certain losses as a component of the war. Therefore, a flail machine may be utilized with a success rate of 80% clearing.
b) *Humanitarian demining* The objective of humanitarian demining is to liberate the whole territory. The threshold of 99.6% land mines for humanitarian demining has been defined by the UN.

3 Landmines detection techniques

Buried landmines can be detected using a variety of methods. The common landmine detection techniques are as follows:

3.1 Biological

The ability to directly sense explosive substances depends upon the biological sensors or biosensors like dogs, certain rodents, sweet bees, plant kinds, and some bacteria types [26]. The livestock employed must be maintained safe, must be subject to set duty cycles, and must be kept untouched. Various biological detection techniques are discussed as follows.

1) *Dogs* Dogs exceed the finest chemical sensors and can identify several by-products from mine's explosive decay but require regular training and reduces their effectiveness with time. Furthermore, they exhibit fluctuations in mood and conduct that are challenging to anticipate [27].
2) *Rats* The use of gigantic African rats as an alternative to dogs is investigated [28]. They are educated with food to show that explosions occur by scratching their feet on the ground. Rat has benefits over dogs: it is cheaper, is available in huge quantities, is smaller, and is resistant to rainy tropical conditions.
3) *Bees* Bees are trained to combine the scent of the explosion with food by distributing a sugar combination and the explosive near the colony. The use of bees is restricted since they can function in fixed

climatic circumstances, and their performance with many sources is challenging to track [26].

4) *Ants* It was observed that ants could detect and transport heaps of explosives (TNT and RDX) to their anthill. Anecdotal evidence is described in [29] and a potential application to generate time-saving smart landmines is presented in [30].
5) *Bacteria:* In the presence of TNT [31] there are genetically engineered bacteria that emit fluorescence. A bacterial detection technique includes spraying and allowing the bacteria to develop in the minefield for many hours and then return to the fluorescence signals for them. Large regions of these bacteria may be covered quickly, but they are susceptible to environmental conditions and false alarms. In addition, there is no known bacterial strain able to detect other than TNT explosives.
6) *Plants* Aresa Biodetection firm has genetically engineered a thale-cress-plant called Arabidopsis Thaliana that alters its color on coming in touch with nitrogen dioxide. This procedure has certain issues: nitrogen oxides are also made up of denitrifying bacteria, which cause false detection, these plants do not get high, which makes it impossible to observe their effects, and worry exists about the contamination of indigenous plants [32].

3.2 Electromagnetic

The electromagnetic radiation method for detecting land mines is established on the dissimilarity between the target electromagnetic characteristics and the ambient terrain [27]. There are several versions or designations used in electro-magnetic methods. The operating frequency, the breadth of the spectrum used, the sent signal type, the interpretation of the reflected signal, or the transmitter and receiver type varies in those versions. The types of electromagnetic detection are given as follows.

7) *Metal detector (MD)* Electromagnetic induction (EMI) forms the basis of MD technology. It contains the main coil (transmitter) and a secondary coil (receiver). The transmitter is adequate in certain combinations. An electromagnetic field is generated by a changing stream in the transmitter coil which induces electrical (eddy) currents in adjacent metal entities. The eddy streams, in turn, cause temporal changes in the receiving coil, which are amplified and processed to indicate landmines. The primary benefit of this technology is that it can identify metal items smaller than 1 cm at 50 cm depth. It has cheap costs and is safe [33].
8) *Ground penetrating radar (GPR)* GPR detection operates by transmitting electromagnetic signals into the ground and detecting the reflected signal. The transmitter transmits a pulsed or continuous wave with the desired frequency. The receptor catches the waves spread in permittivity via the discontinuities. Dismissal can be produced by buried items, such as landmines and natural soil discontinuities (clutter). The principal benefit of this technology is its capacity to identify plastic items buried in the soil. It allows landmines with various types of cases to be found. It may also offer information on the depth of the target. Small metallic scrap is rather unconscious. Unfortunately, several forms of conductive materials like clay significantly attenuate microwave, such that particularly wet clay offers an exceedingly difficult environment. Very dry soils have lower electrical contrast; consequently, such landmines cannot be detected when compared to plastic-boxed landmines [33].
9) *Electrical impedance tomography (EIT)* To build a conductivity distribution chart, EIT utilizes a two-dimensioned set of elements on the ground in which mines are considered anomalies. This technique is particularly suitable for moist soils, as water increases conductivity. EIT is also inexpensive enough to be remotely installed and readily available for enhancing security. The principal disadvantage of the EIT is that direct contact with the soil is required. It is not suitable for usage on arid soils and is sensitive to electrical noise [33].
10) *Millimeter Wave Radar (mmWR)* The mmWR scanning system has been developed to detect buried entities. It is a hyperspectral system that gathers images from a vector network analyzer in various mmWR frequencies (from 90 to 140 GHz) that captures mmWR radiation from a septic tissue. The extraction of valuable information from pictures acquired by this technology involves utilizing a multi-faceted statistical procedure using the principal component analysis (PCA). There were formerly two mmWR landmine detecting techniques: a passive mmWR system based on an efficient temperature of the sky and an active mmWR, which may lead to strong discrimination between landmines and the tiny metal debris. It can detect metallic objects buried under three inches of dry sand [33].
11) *Infrared (IR)* The thermal detection approach is based on the notion that fluctuations in temperature in regions around landmines differ from the surrounding surroundings. Those temperature disparities may be produced by employing high power radiation (i.e., active IR) but involve the risk of

detonation. Factors like weather, landmine dimensions, and composition impact the IR performance. IR sensors are difficult to identify profound objects and more appropriate than individual mines in mined regions. [33].

3.3 Optical

Optical wavelengths are smaller than 1 mm penetrated by optical materials so that optical methods can measure a surface characteristic in the soil that is impacted by the presence. Two typical approaches for optical detection are visible light, and the LIDAR techniques (lights and range detection) are explained as follows.

1) *Visible Light:* Visible light detections include the capture by an optical picture creation system of light waves from visible wavelengths. A visual imager collects a beam of light from an object point and turns it into a beam, converging or diverging from other points, generating a focusing image. Electronic photographs function as transducers that transform the incoming photon energy into electronic output, where the signal is processed and shown electronically. Finally, the visible spectrum fingerprints of land mines might be additionally utilized with spectral filters. The detecting procedure may be carried out from an aerial platform which allows scanning of huge regions in a short period. [32].
2) *LIDAR:* The LIDAR is an optical technology operating in the electromagnetic spectrum in the visible and infrared areas. LIDAR devices deliver consistent radiation pulses that are reflected in a fraction from a laid-down surface item. The sensors monitor the transiting time, and the variation between the transmitted and reflected energy are utilized to determine the distance from the destination as well as its general reflectivity or absorption. LIDAR systems detect the polarization changes in the energy dispersed following illumination of the target by linearly polarized light. This way, surface landmines can be spotted in comparison to the natural surroundings because of their smooth nature. The method is safe, and vast regions may be scanned. It can detect metallic and non-metallic targets throughout the day or night under a wider range of environmental circumstances [32].

3.4 Mechanical

The mechanical methods utilized for landmines often involve machinery to unload, transport or trigger, and destroy landmines. To mechanically detect hidden mines, existing technology is restricted by using a proder, which is manually put into the ground at around 30 degrees [32].

3) *Prodding:* With prodding, a skilled operative protrudes the earth with a stick around 25 cm in length and forms a slight angle with the ground. The region is now being prodded to affirm the existence of mines and is regarded as the only way to ensure a comprehensive detection [32]. The technique is very slow and risky since landmines can have any direction because of soil movements or explosions nearby, and they can be exploited with the [32] sample.
4) *Mine clearing machines:* When an army does not have enough time to clean up a minefield, some robots will frequently roll and clear a safe route. Army personnel uses several types of mine clearers to remove or destroy mines. Some equipment is specially built for mining clearance tasks, while certain mine cleaning systems may also be installed in the tanks. Mine clearance devices are available in wide varieties. New equipment is remotely operated, reducing the risk to staff. It is a fast and effective approach. During demining, persons are less likely to suffer injuries. The area is virtually destroyed, and the machines can miss some mines. The mechanical methods cannot fulfill the humanitarian demining accuracy and safety standards and are not environment friendly [32].

3.5 Acoustic detection

Acoustic waves can serve as a feasible means of detecting and identifying landmines. The ultrasonic and seismic (A/S) acoustic are popular approaches to acoustic detection. These methods are discussed briefly below.

5) *Acoustic to seismic (A/S)* The A/S method is used to determine the landmines, which are created and received by non-contact (acoustic) and contact (seismic) transducers via vibration with acoustic or seismic waves. The mechanical features that may distinguish the acoustic reaction of mines from other items buried in the earth are the basis of this detection method. The transmitter of the A/S system creates the acoustic waves, and the receptor monitors the vibrations. The transmission can have electrically controlled acoustic loudspeakers or shakers. [32].
6) *Ultrasound (US)* The ultrasonic detection involves the release into a media of a sound wave of more than 20 kHz. It is reflected by the limits between materials of various acoustic characteristics. The ultrasound

propagates as a mechanical dis turbance in the form of waves. The wave contains oscillating molecules around the location of the medium, but the matter does not spread, and only the sound energy is transmitted through disturbance and spread. The major benefit of this approach is the US wave's capacity to penetrate very moist soils [32].

3.6 Nuclear detection

A huge number of investigations into the nuclear detection of landmines have been carried out since the 1940s. The common approaches to nuclear detection include nuclear quadrupole resonance (NQR) and neutron-based techniques. These methods are described briefly below [32].

7) *Nuclear quadrupole resonance* This method transmits a radio frequency pulse that excites the explosive nitrogen nuclei and that causes power on a receiver coil. The received response from each explosion is unparalleled and is thus very precise and less vulnerable to false alarms. Its main disadvantage is the poor SNR. The distance between the sensor and the explosion and the temperature is also impacted by radio frequency interference (RFI). [32].
8) *Neutron analysis* In this technique, a continuous or pulsed neutron source emits bursts of neutrons into the ground.

    a) *Thermal neutron analysis (TNA):* In a TNA neutron, gamma rays emanate with an energy unique to the nucleus when absorbed by a nucleus. TNA cannot, however, differentiate nitrogen oxides from those around the explosives, which generates a high number of false detections. The sensitivity is also restricted, the cost is high, and its usage in the field is voluminous and sluggish. [32].
    b) *Fast neutron analysis (FNA):* FNA employs high-energy neutrons to detect and distinguish gamma radiation from various energies. Nearly all components in explosives are sensitive to and identifiable with FNA techniques; however, the equipment typically is difficult and costly [32].
    c) *Pulsed fast neutron analysis (PFNA):* This method uses a neutron pulsed beam with the same FNA idea. PFNA enables the determination of explosive composition, location, and concentration but requires big, bulky, costly accelerators [32].
    d) *Pulsed fast thermal neutron analysis (PFTNA):* This method employs long-lasting beams of neutrons for detection. Its advantages include high reliability and mobile construction [32]. But PFTNA method does not provide sufficient sensitivity to effectively detect the small mines containing explosives in sub-kilogram.

3.7 Magnetometer

The magnetic field intensity and, in some circumstances, field direction, is measured using magnetometers. These are subject to scientific tools. A magnetometer measures the flux density of the surrounding magnetic field. As the magnetic flux density is proportional to the strength of the magnetic field, the output delivers magnetic lines' intensity or strength. Earth is encircled by the streamlines that vibrate at different settings. A magnetometer detects any item or abnormality that alters this magnetic field. The magnetometers can be classified as scalar and vector magnetometers.

9) *Scalar magnetometer* The scalar magnetometer measures the magnitude of the magnetic field. It is further classified as proton precession, overhauled effect, and ionized gas magnetometers.

    a) *Proton precession magnetometer* This magnetometer is based on nuclear magnetic resonance (NMR). The NMR detects the protons' resonance frequency in the magnetic field. The polarized DC stream passes via a solenoid creating hydrogen-rich fuel like kerosene, with a strong magnetic flow. Some protons of this flow are aligned with it. When the polarizing flux is removed, the magnetic field may be measured using the frequency of the precession of the protons for the regular realignment.
    b) *Overhauler effect magnetometer* It operates similar to the proton precession model but uses a low-power radio frequency signal to align the protons instead of the solenoid. In combination with hydrogen, an electron-rich fluid is susceptible to a radio frequency (RF) signal. Protons are connected to the nuclei of the liquid through overhauled action. The precession frequency corresponds to the magnetic flux density and is used to estimate the field's force. This magnetometer consumes less electricity and speeds up sampling.
    c) *Ionized gas magnetometers* This type of scalar magnetometer has better precision than the proton precession. It includes a light and steam photon emitter loaded with vapors such as caesium, helium, or rubidium. The levels of

energy of the electrons, when the atom of caesium meets the lamp photon, vary in frequency with the external magnetic field. The change in frequency gives the magnetic field strength.

10) *Vector magnetometer* A vector magnetometer detects the magnetic field's magnitude and direction. The magnetometers are split into many kinds, such as rotating coil, Hall Effect, magnet resistive, flux, search coil, SQUID, and SERF.

   a) *Fluxgate magnetometer* The fluxgate sensor drive has an alternating drive current that runs a permeable core material. It contains two coils of wire, which are magnetically sensitive. One bow is aroused by the AC delivery, which produces an electric current in the second bow. The current modification is dependent on the field backdrop. Therefore, the alternating magnetic field and the induced current are out of phase. The degree of occurrence depends on the intensity of the magnetic backdrop.
   b) *SQUID magnetometer* It comprises two superconductive systems, divided into two parallel joints by thin isolating layers. These are highly sensitive in low-intensity fields and are most often employed in medical applications.
   c) *Search-coil magnetometer* This type of magnetometer is based on the faraday's slaws of induction. It contains copper coils wrapped around a magnetic core. In the core, the magnetic field line created within the spools magnetizes the heart. The variations of the magnetic field lead to the flux of electric currents, and the voltage changes caused by the magnetometer are detected and recorded.
   d) *Rotating Coil Magnetometer:* The magnetic field produces the sine wave signal in the bob when the coil is spinning. This amplifying signal is proportional to the magnetic field's intensity.
   e) *Magneto resistive magnetometer:* These are semiconductor devices where the electrical resistance varies with the magnetic field applied.

4 Deep learning in landmine detection

The following section studies the impact of deep learning techniques on detecting landmines. The taxonomy of the deep learning to detect the LM is shown in Fig. 3.

4.1 Metal detector

The metal detector identifies the disruption produced by metallic objects in the soil of an emitted electromagnetic field. One of the primary drawbacks of MD is that every metallic fragment generates an alert. The high number of false alarms makes the detection sluggish and costly [34]. Various efforts have sought to improve MD accuracy and lower false alarm (FA) rates. The audio detection signal emitted by the MD in [35] has been changed to simple to comprehend visual representation. In [36], studies have been presented on classification approaches for extracting buried object properties and attributes. In [37], signal theory and pattern matching algorithms are explored, while in [38], the matching of the pursuit of dissimilarity is reported in the combination of the fused clustering algorithm. The target responses utilizing a weighted sum of decaying exponentials were modeled in the [39], whereas the modeling was made using wavelets in [40]. Additional efforts have attempted to combine the signal derived from GPR and metal detectors to enhance detection. For instance, a specialized card was used for the GPR and EMI data collection and multi-kernel methods. Their approach was based on using histograms and local binary functions, among others. In this way, a specialized card was utilized. The work in [41] focused on the data from GPR and EMI data but without classification. Authors have developed a specific automated robot rail setup in [22] to use metal detectors and their output information to build a signature database for buried items with a concentration on land mining. Various methods, including boosting, bagging, and neural networks, are used to categorize entered items properly and differentiate them from other entities. It lets the deminer distinguish between items without depending exclusively on the metal detector sound signals. It thus formulated an entirely automated system that reduces the risk and makes the detection process safer and quicker.

Summary Metal detectors are the most common way to detect underground objects. But their efficiency is limited to detecting landmines with a certain amount of metallic content. So, detecting landmines with non-metallic casings like plastic landmines is difficult using metal detectors.

4.2 Thermal image processing

Thermal imaging technology is frequently used for its benefits in detecting metallic and non-metallic mines [25]. The existence of subsurface mines is recognized by the account of the difference in thermal properties between mine and the surrounding soil. The landmine affects the conduction of heat into the soil that generates temperature distinction [32]. This difference in temperature is detected

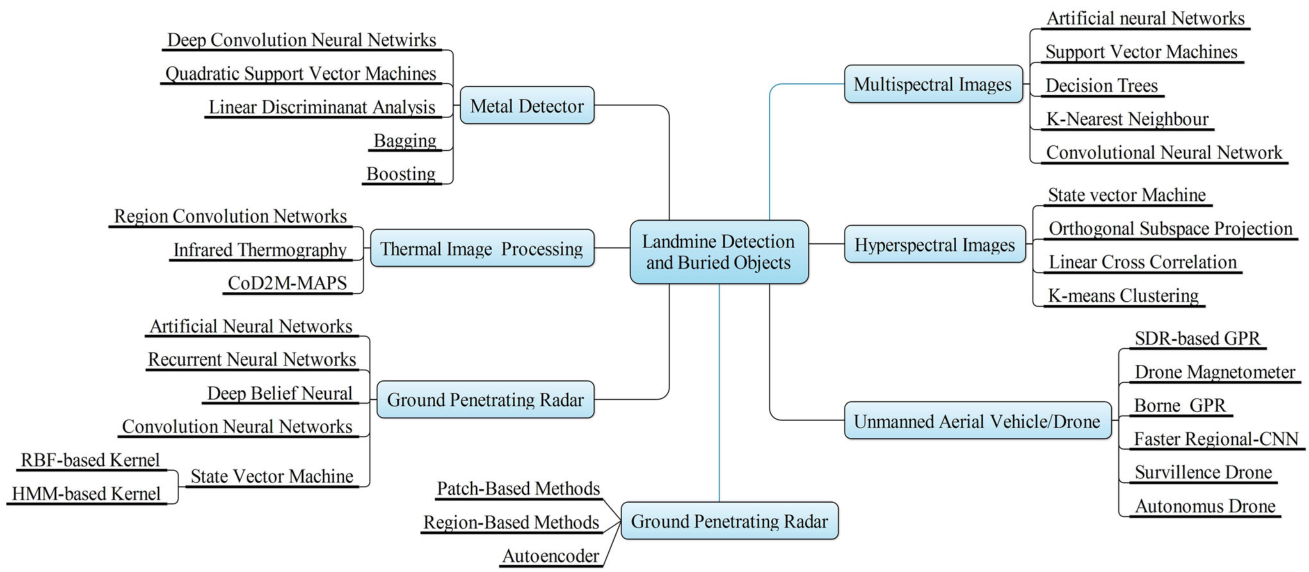

Fig. 3 Taxanomy of the paper

through a thermographic camera that captures the radiations in the infrared (IR) range and is visible in thermal images as a pseudo-color [42]. However, thermal imaging mine detection is difficult owing to the temporary compartment of the soil-temperature distribution throughout daytime and night times [43]. Due to the difficulty of object recognition in thermal images, the necessary techniques for accurately detecting landmines must be developed in image processing.

Several researchers have formulated different strategies to improve the detection of buried mines using thermal IR images. IR images can operate with passive (natural) or active (human) thermal sources. But it is affected by weather and soil moisture. Since the variations in temperature conditions between the bare soil and the ground surface above buried mines are minor, a circular space filter is employed to increase the discrepancies [44]. During sunrise and sunset [45] visibility of buried objects utilizing IR and the charge-coupled camera was discovered to be challenging. Ederra presented mathematical morphology methods for denoise and segmentation of individual images [46]. The rough thermographic sensor image can hardly give adequate information because of sunlight interferences, ground conditions, moisture conditions, etc., and so on. The processing steps of infrared thermography are explained in appropriate technical terms, such as the information acquisition, data pretreatment, anomaly detection, and assessment of the thermal and geometric properties of the detected anomalies [47]. Image processing techniques like the transformation process Karhunen–Loève (KLT), Kittler, and the transformation process Young Transformation have been used to decrease the data size and time in [48], thermal imagery-based mine detections. For landmine detection applications [49] Ajlouni and Sheta have presented KLT and watershed segmentation. Standard and Baertlein [50] created a spectral differentiation idea and a detection method founded on pattern recognition concepts. The behavior of the dynamic scene by time variation and solar illumination cooling during landmine detections and their influence on pictures is analyzed with [51] image processing tools. To identify landmines in outdoor mining field data sets [49], Thanh introduced and approved a finite differential 3-D thermal model. It is found that IR images can reveal the existence of buried objects that can be detected and isolated by appropriate image processing. However, target detection needs additional processing and reasoning for the recognition task as the captured images contained buried rocks, manmade objects, and metals along with the mine [52]. The authors in [23] proposed the region-detection approach of thermal imaging employing RCNN [24] to identify the buried objects and mines. The temperature histogram-based threshold method is used to differentiate the target object in the collected image. The bounding box serves as a zone of interest to identify the hidden object. The RCNN training includes a marked training data set of thermal images with bounding boxes of various forms of buried objects. A dataset of 1000 thermal images with and without objects has been generated by the authors. The RCNN model first includes a selective search where multiple region proposals are generated. Then CNN is employed over the region proposals to generate feature maps that can be used for classification. Finally, the regressor network localizes the target objects using bounding boxes (Table 2).

Summary: Thermal imaging is a passive detection technique, making it relatively safer than other active

Table 2 Landmine detection using GPR

Authors	Problem	Input	Deep model	Methodology adopted	Technique applied	Detection accuracy	Merits	Open issues
Becker et al. [54]	Buried explosive hazards	NA	DBN	Radar array and imaging	Forward-looking GPR	88–93%	1) Improves the detection statistics 2) Reduce number of false alarms 3) In- crease probability detection	Need to disparate temporal fluctuations of target and clutter
Besaw et al. [55]	Buried explosive hazards	B-Scan	CNN	Feature extrac tion	Shallow ANN and Support vector machine	91–95%	1) Lesser false alarms 2) Increased detection proba-ility	Require CNN filters and activation function to better visual ization
Giannaki et al. [56]	Identification and detection	B-Scan & C-Scan	ANN	2D-based finite-difference time-domain	Clutter-removal	92–94%	1) Reduce false alarms 2) remove unwanted clutter	Need to used realis- tic 3D models and real data
Dou et al. [57]	Recognizing and fitting hyperbolae	B-Scan	CNN	Column-connection clustering (C3)	Clustering	95%	1) Robust to noise, effi cacy, and accuracy 2) Fast for real time on site real applications	Segment the weak reflections for small plastic pipes
Lameri et al. [58]	Buried object detection	B-Scan	CNN	Data driven/ feature extraction	Pipeline	95%	1) Work on small image patches with high accuracy 2) Less prone to errors 3) Provide real GPR data	1) Different antenna polarizations effect 2) Need to work di rectly in 3D domain
Bestagini et al. [16]	Identification and detection	B-Scan	CNN	Multi-polarization	Autoencoder/ anamoly detection framework	98%	1) Requires little training and no ad-hoc data preprocessing 2) Different polarizations are used to analyze volumetric data	Improvement is re quired in counting and localizing the threats
Kim et al. [59]	Buried underground object detection	B- Scan and C-Scan	CNN	Image classification	2D and 3D	92–98%	1) decrease the false-positive error 2) empirical judgments are not needed	Need to include full-scale field applications on urban roads

detection methods. But the use of IR imaging is affected by the environmental conditions of the target region.

4.3 Ground-penetrating radar

GPR is a technique used to pinpoint the surface via radar pulses. This is a non-intrusive way of investigating the subterranean utilities of the sub-surface. This non-destructing technique employs electromagnetic radiation in the radio spectrum's microwave band (UHF/VHF) and senses the signals reflected from surface structures. GPR transmits electromagnetic radiation using a transmitter antenna. The major benefit of GPR is the identification of dielectric changes that are helpful not just in the detection of landmines but also for a variety of mine shields. Despite these benefits, the data obtained during the survey must be further processed to enhance and interpret the assessment. The necessity for extensive post-processing work for GPR is, in reality, derived from the poor resolution of GPR signaling and the nature of EM waves transmitted and received by GPR. The processing of GPR data is, therefore, inherently a problem. To address these problems, researchers investigated the following proposals.

In [53], suggested the technique for identifying landmines buried in different circumstances using GPR data. The approach presented employs several characteristics reflecting various properties of landmines that make a landmine more stable to detect and identify. In addition, the depth of the detected landmine can also be calculated utilizing several tests regarding burial depth. Authors in

[54] examined how the deep belief network (DBN) network is a feasible option for the risk of explosive detection in a future-oriented soil-penetration radar system. The new technique used by CNNs to discriminate against buried explosive hazards (BEHs) using GPR B-scans was presented at [55]. In [56], the artificial neural network (ANN) performance was investigated to appropriately reflect some primary features of complicated settings that typically occur during GPR landline detection. In [57] proposed a strategy for automatic detection and hyperbolae fitting for GPR images. The proposed multistage approach also dealt with complex GPR images and detected fit hyperbolic signatures under difficult situations. Lameri et al. [58] proposed a pipeline for landmine detection using GPR B-scan image analysis. In the proposal, convolutional neural networks (CNN) have been used, and the detection is fully automated. Bestagini et al. proposed using a specific kind of CNN known as autoencoder to analyze volumetric data acquired with GPR using different polarizations. The proposed strategy works in an anomaly detection framework, including training autoencoder only on GPR data captured in landmine-free areas. Autoencoders consists of two main components: encoder and decoder. The encoder maps the input data into lower dimensional code or latent representation, while the decoder maps the code to the input. The idea is to learn only the necessary features that represent the input. In the proposed method for landmine detection, the autoencoders are trained in a mine-free area to learn to model the area of interest. During deployment, the autoencoders detect the anomalies generated by landmines as they are non-coherent with the training. Kim et al. [59] studied the underground object classification method using GPR data. The categorization has been made using both B-scan and C-scan images. The 3D GPR data acquired from a multichannel GPR system has been revamped into a 2D grid image consisting of B-scan and C-scan images. 3D shape information of an underground object can be well represented in a 2D grid image. Then deep CNN model was trained using the 2D grid images. The proposed method is validated through field applications on urban roads in Seoul, South Korea.

Pham et al. [60] have adapted a faster-region-based convolution network (Faster-RCNN) model to detect the underground objects using B-scan images. Faster RCNN belongs to the family of RCNN object detection model [61]. But it contains a regional proposal network (RPN) for selecting the region of interest. Also, the input data is processed by CNN layers initially that create the feature map. Then RPN is used to generate the proposals that are later processed by classification and bounding box regression network. It makes it faster and more accurate as compared to RCNN. The dataset involved in the proposed work includes some real-time data along with the simulated data generated using the gprMax [62] tool. In [63] the authors have proposed a deep learning-based model named convolutional support vector machine (CSVM) network that classifies buried objects, shape, and soil type. The proposed model is a combination of CNN layers and an SVM classifier. Pambudi et al. [64] have presented a robust strategy for detecting landmines and UXOs based on pixel-wise likelihood-ratio test (LRT).

Summary The GPR can detect the landmines that have minimum metallic content. Moreover, the technology can detect deeper landmines more efficiently than a metal detector. But the GPR detection is sensitive to surface symmetry and works better for flat surfaces. Also, GPR does not perform well in the area with high water content in the soil.

4.4 2D and 3D detection techniques

In recent years, DL models based on 2D and 3D techniques have grown in popularity. It profits from the advancement of deep learning frameworks in the field of image processing.

1) *2D Detection Technique:* In 2D detection, GPR or other sensed images in the form of 2D data are cropped into small, uniform patches that are used as input for a DL model. Patch-based models, region-based models, and autoencoders are three primary orientations of DL architectures using 2D image data in landmine detection.

   - *Patch-based models* A deep learning-based architecture called deep dictionary learning has been suggested to locate buried objects. Each basic dictionary model was created to calculate the Euclidean distance between a pattern and a dictionary and then use all of the distances as classification representations. The favorable performances of patch-based approaches for detecting distinctive hyperbolic signals were reported by Lameri et al. [58]. and Ishitsuka et al. [65]. In general, DL structures do well in classification tasks that use small regions of 2D image data.
   - *Region-based approach* It uses a GPR image and creates an area of interest (ROI) assigned to one of the classes. ROI areas in a region-based technique are more adjustable than the first method, which uses cropped pictures with a predetermined size. The second direction can more precisely recognize items in B-scan data since a flexible ROI is a rectangular box attempting to define an object's position by its center coordinates and size. A match filter was created

by Dinh et al. [66] to generate possible regions around rebar peaks in 2D data images, and a well-trained CNN identified the possible areas. Besaw et al. [55]. used a 2D median filter and zeros score component analysis to extract ROIs from 2D-based GPR images. A deep CNN was used to classify the extracted ROIs to identify underground explosive hazards. To detect possible hyperbola zones, Lei et al. [67] used a Faster RCNN with a data augmentation method to locate rectangular areas having evidence of underground items. The areas were then converted to binary pictures, and the hyperbolic signatures within them were isolated. Finally, the signatures were used to fit a downward opening hyperbola, and the individual peaks were produced. The findings from work showed that the Faster RCNN generated promising results in identifying ROIs from the GPR B-scan autonomously and effectively. The analysis has been made using synthetic and on-site 2D-based GPR data sets.

- *Autoencoder* Its goal is to convert 2D data into more de- tailed descriptions that make things simpler to understand and detect. Kodagoda [68] suggested an autoencoder net- work to understand underground objects' genuine shapes and positions using 2D image data of synthetic aperture radars. In contrast, to [68], the authors in [69] proposed three different autoencoder architectures to give a unique description of 2D data, in which landmine trances were treated as anomalies. The three designs were symmetric, but their convolutional filters are distinct.

2) *3D Detection Technique:* 3D image data is a space combination of numerous 2D-image data collected from a multichannel GPR system. DL-based technique for under-ground object classification utilizing 3D image-based GPR data was proposed by Kim et al. [59]. A 3D window box, in particular, is used to crop 3D GPR signals acquired by a multichannel GPR system. The clipped 3D data is then used to produce 2D and 3D images. These 2D and 3D images are converted into a 2D orthogonal grid map used to train deep CNN for buried object classification. Similarly, Tong et al. [70]. utilized a CNN-based model to extract feature points from 3D GPR data. For the 3D reconstruction of pavement fractures, these feature points were employed to characterize the contour profiles. The basic principle behind these strategies seems to be transform 3D data into 2D data. When data is transformed, some information is always lost. As a result, utilizing cutting- edge DL architectures that directly utilize 3D data may be a viable solution (Table 3).

4.5 Multispectral and Hyperspectral Imaging

Spectral Imaging is a technique of capturing multiple images of the same target object or area at the different wavelength ranges of the electromagnetic spectrum. It can be further classified as multispectral, hyperspectral imaging (HSI), and ultraspectral imaging. There is no fixed number of images that correspond to a particular class. The hyperspectral image is processed at hundreds of contiguous wavelength ranges that form better resolutions covering a wide range of wavelengths. It is different from multiband or multispectral imaging, with lesser, well-spaced spectral bands as opposed to the continuous one. Ultraspectral imaging is similar to hyperspectral imaging with increased band resolution. The hy perspectral image is captured using various sensors that collect information as a set of images where each image is formed for a narrow wavelength range. It creates multiple images representing values recorded in different spectrums. These images are then combined to form a spectral cube defined by three dimensions: two spatial dimensions describing the coordinates in space and one spectral dimension representing the range of wavelengths. This data cube, representing a hyperspectral image (HSI), can be processed and analyzed to extract some knowledge from the captured data. The spectral bands at the various wavelength range of the electromagnetic spectrum can be considered for HSI.

In [71], researchers investigated different algorithms for target detection using hyperspectral images. Authors divide these algorithms into two classes: supervised and unsupervised. In supervised algorithms, a known spectrum depicts the target, while in unsupervised algorithms (anomaly detectors), pixels distinct from their surrounding area are considered targets. The target detection in hyperspectral imagery is an active research domain. The authors in [72] investigated the model of the hyperspectral imaging over practical algorithms for target detection. Similar to [72], authors in [73] studied the model of the hyperspectral images in the radiance domain. Here, the authors' target is to convert the reflectance spectrum into a radiance value after estimating atmospheric transmission and scattering parameters. It has been used to minimize the time required for computation. But, the predicted radiation spectrum accuracy depends on the accuracy of the computed atmospheric parameters. To address this problem, authors in [74] proposed a method for subpixel target detection based on supervised metric learning. The algorithm works by maximizing the distance between the target and the background materials while restraining the propagation of

Table 3 Landmine detection using UAV

Authors	Problem	Architecture	Methodology adopted	Detection accuracy	Merits	Open issues
Colorado et al. [93]	Terrain mapping and geo-detection	NA	Computer vision algorithms within a low-cost UAV robot suited	90–94%	1) Provide real time detection 2) Generate a mosaic image of a current terrain	Speed and Height of the UAV need to be maintained
Cerquera et al [94]	Landmine detection	Down looking GPR	SDR-based GPR	92– 94%	1) Increased the detection by means of reducing the interference	Need to cover the more area
Schartel et al [98]	Detect landmines, cluster munition, grenades, and IEDs	Side looking GPR	Circular synthetic aperture ground penetrating radar (SAGPR)	98%	1) examines the coherent su perposition of data from circular apertures at different heights 2) detect the deeply buried anti-tank mines and anti-personnel mines located just below the surface	1) Required to create a systematic database 2) Needed to improve the detection algorithms
Fernandez et al. [7]	Detection and imaging of buried targets	Down looking GPR	SAGPR	95– 98%	1) Safety and faster scanning speeds 2) detect both metal-lic and non-metallic targets	Detection of buried civil infrastructure is needed
Šipoš et al. [91]	Buried landmines in harsh terrain	Down looking GPR	Stepped frequency continuous wave (SFCW) GPR	95– 98%	Usable for harsh environ ments	Improvements for a fully operational system regarding different aspects of scanning speeds and soil properties such as mois ture content
Almutry et al [99]	Buried hazardous explosives	Down looking GPR	Tomographic synthetic aperture radar	95– 98%	Increase the penetrating depth and obtain higher resolution	Need to extend to remote sension applications
Baur et al [21]	Landmine contamination detection and mapping	NA	Faster R-CNN	99.30%	1) training and testing volume data is increased 2) optimize detection across different environmental conditions	Need to develop a completely automated processing and interpretation package

similar pixels. In [15], authors used hyperspectral imaging to identify landmines and discussed several signal processing algorithms for hyper-spectral image processing and target detection used in this context. In [75], authors proposed the comparative analysis among different algorithms (adaptive coherence estimation [76], Matched Filter [72], Constrained Energy Minimization [77], Multiple target CEM [77], Winner take all CEM (WTACEM), Orthogonal Subspace Projection [78], Spectral Angular Map- per [79], spectral information divergence [80]) in different scenarios to study their performance in landmine detection. The algorithms do not support the detection of multiple targets simultaneously. Thus when dealing with multiple targets, the algorithm must be used for several runs, each searching for a specific target. This result in high computation time if the number of targets is high.

Some algorithms have been extended to the multi-target case, like CEM. It can detect plenty of targets in a hyperspectral image. Many algorithms are extended from CEM, e.g., MultiCEM, SumCEM, WTACEM, and others [81]. Golovin et al. [82] have proposed a landmine detection method with the help of long-wave infrared (LWIR) hyperspectral data. The au thors have used the multi-angle hyperspectral camera mounted over a UAV that senses the target area where landmines are buried. Khodor et al. [83] proposed a pixel similarity method to improve landmine detection in hyperspectral images. The idea is to pick only highly distinct pixels as potential targets before applying a state-of-the-art target detection algorithm.

Summary Spectral imaging can capture the features at multiple channels, which results in better detection ability. Like GPR, they can also detect non-metallic landmines at much deeper depths. But the cost involved with acquiring and processing the data in spectral imaging-based detection is very high.

4.6 UAV/DRONE-BASED detection

Unmanned aerial vehicles (UAVs), usually called drones, have been developing extensively in recent years owing to advancements in avionics and propulsion systems, battery capacity, independent navigation, and easy sensing integration. In addition, the cost reduction of these devices enabled UAV use in various areas, such as precision agriculture and the forestry surveillance of [84, 85], ground surveillance and mapping [86] and electromagnetic compatibility and antenna measurements of [87]. UAVs can also be utilized for network coverage and improved data communication. UAV-based landmine detection systems for the non-destructive survey and the imaging of subsurface objects have been developed through these developments in UAV technology. Some of the main benefits of UAV-based detection include [88]: (i) the ability to scan regions that are difficult to access, (ii) the ability to scan areas that are difficult to reach, (iii) decreasing the danger of unintentional explosion.

In recent years, several UAV-based detection methods and sensor concepts have been examined. In [89] the optical detection of partly buried mines and cluster munitions is studied. Cameras are ideal for identifying surface hazards, but such sensor types fail for underground or concealed mines. Authors in [90] used UAV-mounted fluxgate vector magnetometers to identify unexploded ordnance (UXO). However, magnetometers and metal detectors cannot reliably identify modern minimal metal mines. A GPR is a measurement instrument capable of generating surface images of minimal metal mines.

In [91, 92], authors used the UAV-based down looking GPR (DLGPR), which is a low cost lightweight stepped frequency continuous wave radar working in the 550–2700 MHz frequency band. In contrast to [91] and [92], authors in [93] and [94] studied the impact of integrating software-defined radio (SDR) with the GPR. In [95] investigated the use of a commercial GPR which works at sub-GHz frequencies, thus providing better penetration depth but at the cost of decreased spatial resolution. However, a DLGPR tends to scan line by line, which means limited area output and low throughput. Also, the authors found that objects buried just below the surface are exceedingly difficult to detect due to the high soil reflection. A side looking GPR (SLGPR) can be used to overcome these issues. A long synthetic aperture helps in the formation of high-resolution 2D-radar images. But, using a linear aperture, there is an ambiguity problem in range direction and depth. It can be resolved by either a nonlinear motion trajectory of the UAV, e.g., a circular synthetic aperture radar (CSAR), or by cross-track interferometric SAR (InSAR), or repeat pass tomography [96]. In contrast to [96], authors in [97], studied the 3D GPR-SAR imaging. The working frequency band ranges from 300 MHz to 5 GHz, as it provides a good tradeoff between spatial resolution and penetration depth. In [98] the authors examined the coherent superposition of data from circular apertures at different heights. In the UAV-based GPR systems, the extension from 2 to 3D scans is still limited by the flight autonomy of the UAVs. In most of the contributions, the selected UAV provides an average flight time of 15 min. Thus, the survey of bigger regions would require additional platforms such as wire-powered UAVs.

Almutry et al. [99] investigated the tomographic synthetic aperture radar (TSAR) to identify and localize the landmine. Baur et al. [21]. concentrated on the development and testing of the automated strategy for remote landmine detection and identification of scatterable anti-personnel landmines in wide-area surveys. The authors employed the supervised learning using the Faster Regional-Convolutional Neural Network (Faster R-CNN) to achieve the target. Alvey et al. [100]. have also used a deep learning-based model for the explosive hazard detection in aerial survey. For this, the authors have used a simulated dataset developed using Unreal Engine with Microsoft Airsim plugin [101].

Summary: UAV-based detection helps reduce the risk involved and the time required to detect the landmines. Resource constraint is a significant challenge that requires efficient path planning and communication. The security of the UAV data transmission is another hurdle that must be handled effectively.

5 Open issues and challenges

The automated detection and localization of landmines and buried objects are still in their infancy. Various open issues and research challenges need to be handled to improve the detection of the landmines. This section discusses the challenges associated with landmine detection.

1) *Noise:* The process of capturing the readings with the help of a sensor attached to the carrier vehicle is influenced by various factors such as carrier movement, environmental factors, etc. It can lead to the addition of some noise in the captured data.
2) *Clutter:* The presence of underground clutter along with the landmines makes the detection challenging.

Clutter makes it difficult to determine the mine signature in the target region.

3) *False Alarm:* Depending on the region of operation and the existing cluster, there can be various signatures that are not landmines but are detected as such. It increases the time and effort required for minefield clearance.
4) *Dis-localization of landmine Signatures:* Since various factors are involved in capturing the readings during the survey, there can be some shift in the observed signature of the landmine from its original deployed location that can hamper the detection accuracy.
5) *Missing Landmine Signatures:* As different deployment strategies are used to deploy different types of landmines in varying regions, it may be possible that the signatures of some landmines are missing in the captured data. It poses a severe risk for the mine removal team.

6 Conclusion

In this paper, we have reviewed various landmine detection approaches. Our study contributes to state-of-the-art immensely as we provide a systematic survey on deep learning contribution in this field. We have looked extensively into how deep learning can be integrated with landmine detection approaches as a revolutionary approach in technology. We have covered the techniques and classifications of landmines. We have analyzed different types of landmine detection techniques and identified the pros and cons of each of them. We have paid great attention to survey GPR as the most widely used detection technology and UAV applications as an effective automation enabler to address this problem. We also investigated magnetometry imaging technology as it has become a trending technology since it was integrated with cost-effective UAV solutions. Our research group is striving toward developing an automated deep learning-based solution that integrates several technologies relevant to imaging and automation. Our system will address the capturing and processing sensed imagery taken using magnetometry technology. We should address various relevant aspects themed around the challenges of such integration.

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Author's contributions The work is done by equal cooperation of authors.

Declarations

Data availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflict of interest Authors declare that they do not have conflict of interests.

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