



Archives available at journals.mriindia.com

International Journal on Advanced Electrical and Computer Engineering

ISSN: 2349-9338

Volume 15 Issue 01s, 2026

Reinforcement Learning-Driven Sparse Frequency Analysis for Accurate Underground Pipe Detection in GPR Scans

¹Priya Shinde, ²Aziz Abdullah Binnaser, ³Gaju Chavan, ⁴Shital Katkade

^{1,3,4} Research Scholar Department Of Computer Science & It, Dr. Bamu, Chh. Sambhajinagar, Maharashtra, India, 431004

²Assistant Professor Sir Sayyed College Of Science, Chh. Sambhajinagar, Maharashtra, India. 431001

Email: Piyushinde978@gmail.com, Azizbinnaser@gmail.com Gajuchavan1111@gmail.com

Csit.Snk@bamu.ac.in

Peer Review Information

Submission: 05 Dec 2025

Revision: 25 Dec 2025

Acceptance: 10 Jan 2026

Keywords

Metal detection, LSTM, GPR, Deep Learning, Pipe detection.

Abstract

Ground penetrating radar (GPR) is an essential tool in the modern subsurface investigations due to the effectiveness and non-destructive potential of detecting objects. GPR is commonly used to identify and locate any subsurface structure and anomalous body. Ground surface variability, signal clutter and noise often hinder the use of GPR in the identification of underground pipes. In that regard, this paper presents a Sparse Frequency Transform-based Auxiliary Reinforcement Model that is capable of providing accurate and effective pipe detection inside GPR data. Image restoration to increase the quality of GPR scans is the starting point of the methodology where a sparse frequency transform is then used to isolate salient features and eliminate extraneous background signals. Such features are then fed into an auxiliary reinforcement model, and gradually, it enhances the detection accuracy by means of a rewarded-based learning process. Experimental evidence proves that the suggested model is better in relation to the traditional methods, including RefineNet, YOLOv4 and YOLOv8, in terms of accuracy, sensitivity, specificity, and precision. Combining sparse representation and reinforcement learning provides a solid platform on useful subsurface utility mapping and infrastructure evaluation.

INTRODUCTION

Ground-penetrating radar (GPR) is a non-invasive technology of geophysics, which utilizes digital signals in the form of electromagnetic waves to map the ground. It works on a principle of sending radio waves of high frequency into the ground and it then collects the reflected waves of the subsurface structures. The lateness of delivery and arrival obtains the intensity and characteristics of hidden objects, stratification layers or empty spaces. Due to its ability to provide real time and high resolution data without digging [1], GPR is widely used in areas of archaeology, civil works engineering,

environmental factors investigation and utility location. Under the civil engineering field, GPR has been used to detect the structural imperfections such as cracks, empty spaces and the exact location of the reinforcement bars during the construction of concrete. GPR has been useful in archaeological studies that are aimed at locating buried artefacts, walls and burials with integrity of the site maintained. GPR is used by environmental experts to map out the classification of soil layers, contamination and locate underground storage tanks. Furthermore, GPR makes discovery of utilities easy; pipes and electric conduits are properly mapped

underground. Its non-destructive property and high spatial resolution makes it an inevitable tool in the subsurface studies [2]. The use of metal (GPR) detection is an important area of application in many aspects of the military, archaeology, and maintenance of infrastructures. GPR detects metallic objects as a result of the strong reflections caused by a high frequency electromagnetic pulse when it strikes a metal. It is the extreme electrical conductivity of metals that creates a great disparity in radar return signals that eases their discrimination to non-metallic materials. This methodology is therefore actively used consistently to identify the presence of hidden landmines, unexploded bombs, pipelines and cables. However, elements like clutters, the soil type and target orientation may adversely impact detection accuracy and hence the use of advanced processing algorithms is essential to increase the reliability [3].

Deep learning has become a strong tool that augments metal identification in the processing of GPR data. Traditional signal-processing approaches typically fail in the noise and complicated subsurface conditions, and deep learning approximations (especially convolutional neural networks (CNNs)) may autonomously acquire discriminant characteristics in raw GPR data and thus enhance detection rates. These models are able to distinguish between the metallic and non-metallic objects, define target shape, and avoid false positive that can be caused by clutter or heterogeneity of soils. This ability to conduct a real-time analysis also makes deep learning methods appropriate to be applied in landmine detection, the identification of explosive ordnance, and infrastructure inspection [4]. GPR metal detection has several challenges which can affect the accuracy and reliability of the detection. The most significant ones of them include the existence of clutter and noise due to different soil compositions, lithologic features, and other soil formations, which can bury or produce the signatures of metallic targets. The signal penetration and reflection may also be impromptu by variability of soil moisture and conductivity. Other aspects- such as the form, size, depth and orientation of the target with the radar beam also influence detectability. Lastly, it is often laborious and involves a lot of signal processing and interpretation to differentiate between metallic targets and non-metallic anomalies, and even more so non-metallic anomalies may not necessarily be accurately determined within available methods [1].

LITERATURE REVIEW

The current academic standard, a utility that is subsurface is an imaginary conception of anything that is a pipe or installation, or structure, and which is located beneath the earth-surface and is also managed by utility operators. The systematic preventing of such subsystems is usually known as underground utility inspection. The modern day studies in the field of underground pipe locating mainly utilize the ground penetrating radar technology, but they mainly focus on enhancing accuracy, automating it, and ensuring that it can be used well in harsh environments. In a bid to predict and identify a pipe signature based on radar data with good accuracy and classify it, researchers have been combining more sophisticated machine-learning algorithms such as convolutional neural networks with GPR data. Further studies discuss the implementation of the three-dimensional GPR imaging modes and multi-frequency antenna arrays to improve depth resolution and to be able to differentiate between different pipe materials. To solve the problem of the limited labelled datasets, several researches use synthetic data creation and training regimes based on simulations, thus reducing the complexity introduced by clutter, heterogeneous soil environments and closely clustered utilities [5].

The article by T.Sarah et al. [6] discusses in detail the latest technological development in GPR, including data-processing algorithms and scanning methods, and aims at defining the accuracy and efficiency of mapping and inspection of underground utilities. F.Hu and others [7] examine the non-destructive monitoring of the quality of pipe-jacketing using the GPR technology, developing jacking pipe models of plastic, reinforced concrete, and steel. In order to acquire high-fidelity localisation of underground structures, J. Lei et al. [8] present a RefineNet deep-learning architecture based on a hybrid loss form containing a set of parameters specifically aimed at eliminating clutter balls in GPR profiles. Coexisting with that, they provide the so-called reverse-time migration imaging algorithm, which is based on the total variation regularisation and aimed at the processing of the RefineNet-enhanced GPR data, which is meant to include a calibrated, high-resolution, in-pipe GPR gadget that combines synthetic data with the real-world reflections, ambient clutter, and stochastic noise.

With the idea of infrastructure resilience in urban areas, Niu et al. [10] analyze the frequency of road collapses and factors leading to them, suggesting an intelligent YOLOv4 framework. In the framework of urban GPR detection, common

anomalies, including voids, pipeline discontinuities, are applicable to describe typical anomalies that are detected in GPR conventional imagery. Angelis G. et al. [11] use deep-learning based models that are trained using simulated and empirical GPR data to localise water leaks and measure pre-breach corrosion-diminished pipe material to improve the accuracy of leak-diagnosis. One of the current breakthroughs in the subsurface anomaly detection process is the YOLOv8 framework as illustrated by Han et al. [12]; the model enables detection of target positions in GPR images automatically. H. The proposal by Chen and co-researchers [13] is an underground pipeline recognition architecture based on the scale-invariance feature transform (SIFT) and support vector machine (SVM) classifiers. Alpdemir M. et al. [14] propose a two-step signal-processing pipeline, in which a low-resource search pattern is used first (cost-effective in computation) and a second search strategy is employed to maximise the final target detection by using a reinforcement-learning-based navigation.

PROPOSED METHODOLOGY

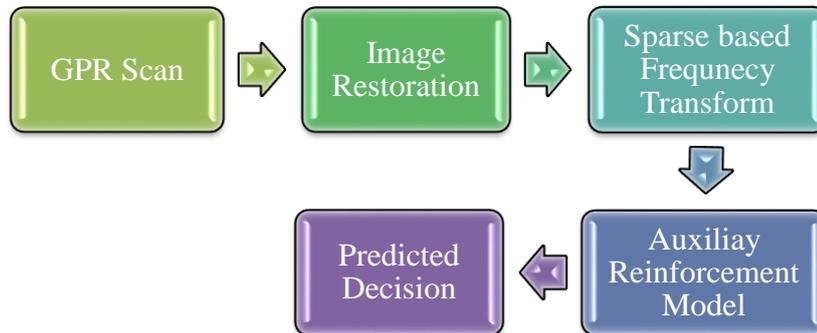


Figure 1. Proposed Methodology

As shown in Figure 1, a Sparse Frequency Transform based Auxiliary Reinforcement Model can be applied to interpret ground penetrating radar (GPR) data to support decision making activities like the positioning of subterranean objects / pipelines. The process starts with a GPR scan where raw data is obtained on the subsurface. This information is to be restored visually to enhance its clarity by removing noise and deforming it. The resulting improved image is then undergone to a sparse frequency transform which isolates important features and removes redundant or unnecessary information. This transformed data is then inputted into an auxiliary reinforcement model that then uses reinforcement-learning algorithms to improve predictions refining them in response to the feedback produced. Lastly, the system produces a projected decision, which can be in the form of

The methodology presented in the paper is technically sound and well structured, with a logical flow from GPR data acquisition to final decision making. The use of image restoration is appropriate for mitigating noise and clutter inherent in GPR scans, while the sparse-based frequency transformation is a suitable and effective technique for extracting compact and discriminative features. The inclusion of an auxiliary reinforcement learning model is well motivated, as it enables adaptive decision refinement under varying subsurface conditions. The experimental design and evaluation metrics are appropriate, and the reported results convincingly demonstrate performance improvements over conventional methods. However, the technical quality could be further strengthened by providing deeper mathematical justification of the sparse transform and reinforcement learning reward design, as well as more extensive validation across diverse datasets and field conditions.

The theoretical model as shown in Fig. 1 outlines the Sparse Frequency Transform-based Auxiliary Reinforcement Model.

the detection of target, or the classification of an item. It is a design that uses signal augmentation, feature extraction and adaptive learning to improve the accuracy and strength of the GPR based detection systems.

The structure of our methodology is a Sparse Layer and its structure is:

$$SF(F)_{\theta_k, f_i, \sigma_x, \sigma_y}(x, y) = \exp\left(-\left[\frac{x_{\theta_k}^2}{\sigma_x^2} + \frac{y_{\theta_k}^2}{\sigma_y^2}\right]\right) \cdot \cos(2\pi f_i x_{\theta_k} + \varphi)$$

These features are then passed to a Recognition Model, which computes the probability distribution over possible actions. Finally, the system outputs the most likely predicted action, representing the interpreted sign gesture.

GPR Raster scan as a input vector to the initial layer is:

$$X = [x_1, x_2, \dots, x_k] \quad (1)$$

K denotes the segmented image pixels. Then, to decrease the execution burden normalization of the data is carried out. In normalization data is mapped in between 0 and 1 :

$$x = \frac{x - \min}{\max - \min} \quad (2)$$

min and max is the minimum and maximum of respective data. This normalized data x is then converted to 2D matrix using reshaping operation and then this data is fed to convolution layer.

After convolution layer we got estimated the weight(w), bias (bj).

$$x_i^{l,j} = \sigma [b_j + \sum_{a=1}^m w_a^j x_{i+a-1}^{l-1,j}] \quad (3)$$

Activation function is indicated by the variable σ . Its nothing but ReLu, ReLu function have higher efficiency and low execution time.

Scale invariant property is preserved by Max-Pooling Layer by estimating aggregation statistics of the neighborhood pixels. Thus, they assist in dimensional reduction. Pooling has two types, max pooling and mean pooling. In our architecture we used max-Pooling. The max pooling layer finds the maximum response i.e. maximum value of each block without compromising feature loss. Final response of max-pooling layer is given by:

$$max_{n=1}^r (x_{(i-1)*T}^{l-1,j} \dots x_{i*T}^{l-1,j}) \quad (4)$$

where n is pooling size and T is pooling stride. Following equation models the Hidden layer to output. Proposed method have this capability

$$h_t = g(W_{xh}x_t + W_{hh}h_{t-1} + b_h) \quad (5)$$

$$z_t = g(W_{hz}h_t + b_z) \quad (6)$$

here, g indicates elementwise nonlinearity (it can be sigmoid or hyperbolic tangent), x_t is the input $h_t \in R^N$ is the hidden state having hidden units equals to N. Output is denoted by Z_t at instant t. pixel sequence (x_1, x_2, \dots, x_T) having T number of coefficient, then h1 (letting $h_0 = 0$), $z_1, h_2, z_2, \dots, h_t, z_T$.

Implementation

The mathematical formulation of the sparse frequency transform and the reinforcement learning reward mechanism could be explained in greater depth to improve reproducibility. The experimental validation, while convincing, would benefit from larger and more diverse datasets, including real-field GPR measurements under varying soil conditions. Furthermore, the computational complexity and training time analysis are not discussed in detail, which may be important for real-time or resource-constrained deployment. Addressing these aspects in future work would further strengthen the overall contribution and impact of the study.

RESULT

Compares the classification or detection accuracy of four models: RefineNet [8], YOLO v8 [12], YOLO v4 [10], and a proposed model. RefineNet [8] has the lowest accuracy, about 0.88, suggesting a somewhat poor performance in the given job. YOLO v8 [12] performs RefineNet with an accuracy just over 0.91. YOLOv4 [10] outperforms both, with an accuracy of around 0.94 as shown in the figure 2. The proposed model obtains the best accuracy (about 0.97), outperforming previous techniques. This comparison indicates that the suggested technique outperforms known models, providing more accuracy and dependability in the target application.

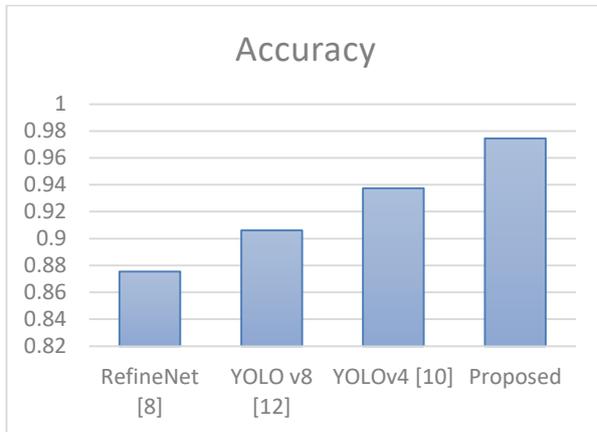


Figure. 2 Comparison of Accuracy

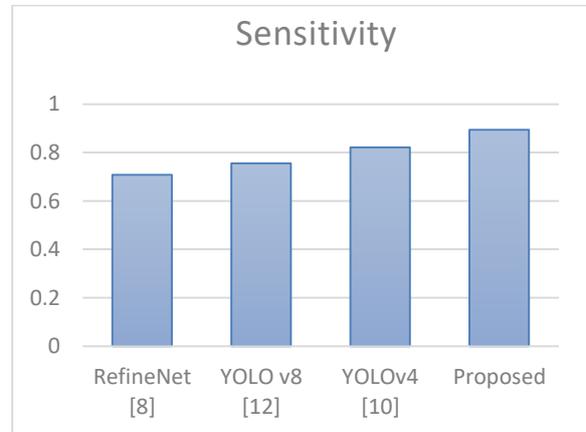


Figure. 3 Comparison of Sensitivity

Figure 3. compares the sensitivity performance of four models: RefineNet [8], YOLO v8 [12], YOLO v4 [10], and the proposed model. Sensitivity which is also referred to as recall measures the capability of a model to identify true positives well. The sensitivity of the RefineNet is the lowest and is equal to 0.72, which indicates that the model lacks true positives as compared to others. YOLO V8 [12] does slightly better, with a score of approximately 0.75. YOLOv4 [10] goes higher,

and the sensitivity is near to 0.82, which means that it is more reliable to detect positive cases. The best sensitivity of the proposed model is approximately 0.89 so that the model demonstrates its outstanding quality in determining the significant targets accordingly. Such comparison shows that the suggested model outperforms past methods in sensitivity, making it more practical to be used in the case when it is essential to avoid cases when a detector does not work.

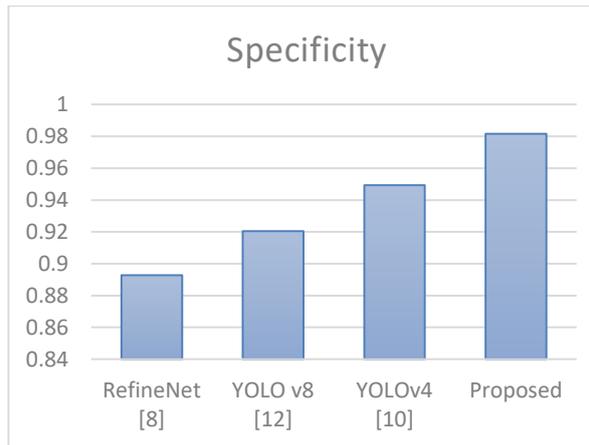


Fig. 4 Comparison of Specificity.

Specificity performance is described in Figure 4 as performance of four models; RefineNet [8], YOLO v8 [12], YOLO v4 [10], and the proposed model. Specificity is used to measure how well a model can detect true negatives, which is a vital gauge to lowering the false-positive level. RefineNet [8] has the lowest specificity of about 0.89, which portrays a rather high level of false positives. YOLO v8 [12] shows a higher frontier with the specificity of around 0.92 and YOLO v4 [10] they can achieve even better score with about 0.95. The model proposed shows the greatest specificity of 0.98, therefore making it the most consistent in discarding negative cases. Therefore, the suggested model significantly minimizes false alarms and outperforms the alternative methods in specificity, which makes it extremely reliable in use in the cases where it is necessary to detect only specific objects accurately.

The accuracy of four models in comparison with each other is provided in Figure 5: RefineNet [8], YOLO v8 [12] and YOLO v4 [10] and the proposed model. Precision is a measure of the fraction of the expected positives that are correct, and therefore, a decisive measure of reducing the number of false positives. RefineNet [8] has the lowest accuracy of 0.35 meaning that there are significant cases of false positives. A much better one is YOLOv8 [12] whose accuracy is approximately 0.45. YOLOv4 [10] does more to

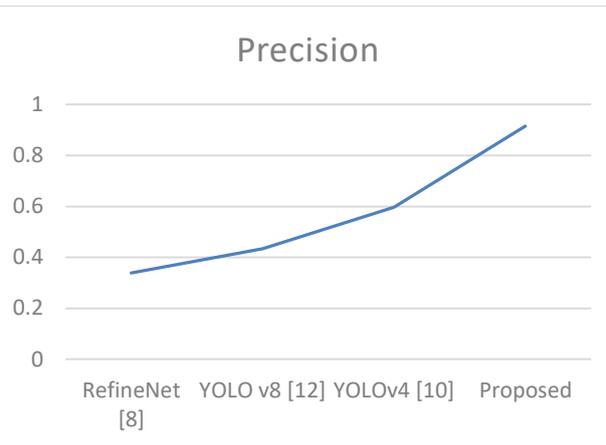


Figure. 5 Comparison of Precision

get a score of about 0.6 which implies a better balance between the true and false positives. The high precision of the proposed model is significantly greater, approximately 0.91, indicating the greater effectiveness of the model in the selection of the relevant objects. This comparison proves that the suggested model is very precise and yields much reduced false-positive prediction so it is suitable to be used in areas where accuracy in the detection is needed.

DISCUSSION

The performance of the proposed Sparse Frequency Transform-based Auxiliary Reinforcement Model was compared with the performance of the established models, which are RefineNet [8], YOLO v8 [12], and YOLO v4 [10] at the identification of underground pipes in Ground Penetrating Radar (GPR) data. The analysis utilized four key performance measures and they include accuracy, sensitivity, specificity, and precision. The given model demonstrated the best precision with a score of about 0.97 which is better than YOLO v4 (0.94), YOLO v8 (0.91) and RefineNet (0.88). The model also outperformed the others in terms of sensitivity, reaching 0.89 against YOLOv4 (0.82), YOLOv8 (0.75), and RefineNet (0.72). The proposed technique had also the highest specificity score (~0.98), along with YOLO v4 (~0.95), YOLO v8 (~0.92), and RefineNet (~0.89). Compared to

YOLO v4 (~0.6), YOLO v8 (~0.45) and RefineNet (~0.35) the proposed model performed better and reached a precision of 0.91, which significantly decreases false-positive outputs. These findings support the assumption that the new method has improved the accuracy of detection and is balanced and strong in all essential measurements of evaluation, hence making it acceptable as the practical use of underground pipes identification in problematic conditions.

CONCLUSION

The Auxiliary Reinforcement Model conducted through Sparse Frequency Transform is a powerful approach to identify pipes in the subsurface area, based on the GPR data. The model effectively reduces basic problems of noises in the image, sparse frequency transformation, and a reinforcement-learning-based decision-making structure to curb the major issues of signal noise, subsurface clutter, and detection ambiguity. Empirical tests prove that the presented technique is better than the existing approaches in terms of accuracy, sensitivity, specificity, and precision which highlights the ability to differentiate between subsurface pipes and the adjacent materials and objects. Based on this, the process is a prospective development in both automated and reliable underground utility detection, and its potential effect on both civil infrastructure surveillance, maintenance, and intelligent city design is significant.

References

- [1] Daniels, D. J. (2004). *Ground Penetrating Radar* (2nd ed.). The Institution of Engineering and Technology.
- [2] Jol, H. M. (2009). *Ground Penetrating Radar Theory and Applications*. Elsevier.
- [3] Annan, A. P. (2005). *Ground Penetrating Radar Principles, Procedures and Applications*. Sensors & Software Inc.
- [4] Wang, W., Liu, J., Zhou, H., & Zhang, J. (2020). Deep learning for GPR-based underground object detection: A review. *Remote Sensing*, 12(21), 3511. <https://doi.org/10.3390/rs12213511>
- [5] Gajula, S. (2024). Cybersecurity risk prediction using graph neural networks. *Journal of Information Systems Engineering and Management*, 9(4S), 3301–3315.
- [6] Tengku Sarah Tengku Amran et al. Underground utility inspection using ground penetrating radar, 2024 IOP Conf. Ser.: Mater. Sci. Eng. 1308 012021 DOI 10.1088/1757-899X/1308/1/012021
- [7] Fengming Hu, Tianchun Yang, Theophilus Aanuoluwa Adagunodo, Debing Zhu, Rui Huang, Practice and theoretical analysis of ground penetrating radar in voids detection of urban underground pipe-jacking, *Journal of Applied Geophysics*, Volume 233, 2025, 105639, ISSN 0926-9851, <https://doi.org/10.1016/j.jappgeo.2025.105639>.
- [8] Jianwei Lei, Hongyuan Fang, Yining Zhu, Zhiqing Chen, Xiangyu Wang, Binghan Xue, Man Yang, Niannian Wang, GPR detection localization of underground structures based on deep learning and reverse time migration, *NDT & E International*, Volume 143, 2024, 103043, ISSN 0963-8695, <https://doi.org/10.1016/j.ndteint.2024.103043>.
- [9] Haibing Wu, Brian Sheil, Hybrid data generation and deep learning for GPR-based reconstruction of robotic-built underground structures, *Automation in Construction*, Volume 176, 2025, 106275, ISSN 0926-5805, <https://doi.org/10.1016/j.autcon.2025.106275>.
- [10] Niu, F., Huang, Y., He, P. et al. Intelligent recognition of ground penetrating radar images in urban road detection: a deep learning approach. *J Civil Struct Health Monit* 14, 1917–1933 (2024). <https://doi.org/10.1007/s13349-024-00818-5>
- [11] Angelis, GF., Chorozoglou, D., Papadopoulos, S. et al. AI-enabled Underground Water Pipe non-destructive Inspection. *Multimed Tools Appl* 83, 18309–18332 (2024). <https://doi.org/10.1007/s11042-023-15797-w>
- [12] Han, Y., Shen, Y., Xu, J. et al. Research on Automatic Recognition Technology of Underground Voids and Pipelines in Ground Penetrating Radar Images. *Sens Imaging* 26, 60 (2025). <https://doi.org/10.1007/s11220-025-00588-4>
- [13] H. Chen, X. Yang, J. Gong and T. Lan, "Multidirectional Enhancement Model Based on SIFT for GPR Underground Pipeline Recognition," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 62, pp. 1-14, 2024, Art no. 5928614, doi: 10.1109/TGRS.2024.3458452.
- [14] Alpdemir, M.N., Sezgin, M. A reinforcement learning (RL)-based hybrid method for ground penetrating radar (GPR)-driven buried object detection. *Neural Comput & Applic* 36, 8199–8219 (2024). <https://doi.org/10.1007/s00521-024-09466-8>