# Automatic Target Detection Using Ground Penetrating Radar (GPR) Data Based on A Machine Learning Approach: A Survey

**Gaurav R. Savade**

Department of Electronics and Telecommunication, Babasaheb Naik College of Engineering Pusad, Karla Road, Pusad, Maharashtra, 445215, India.

---------------------------------------------------------------------***---------------------------------------------------------------------

**Abstract -** Ground Penetrating Radar (GPR) is a valuable tool for subsurface exploration across diverse fields such as archaeology, defence, and civil engineering. Traditionally, GPR data has been interpreted manually, requiring extensive expertise and being time-consuming. Recently, machine-learning approaches have emerged as effective solutions for automating target detection, significantly reducing time and human dependency while enhancing accuracy. This review provides a comprehensive overview of the current advancements in automatic target detection using GPR data, focusing on machine learning-based methods. We summarize feature extraction techniques, popular machine learning algorithms, and challenges within this domain. This paper also identifies future directions and potential improvements for robust, accurate, and efficient GPR-based automatic target detection systems.

***Key Words*:** Machine Learning, Ground Penetrating Radar, Object Detection, Signal Processing.

## 1. INTRODUCTION

Ground Penetrating Radar (GPR) is a non-destructive electromagnetic (EM) subsurface probing technique used in fields as diverse as geophysics, defence, archaeology, environmental science, and infrastructure inspection. By emitting high-frequency EM waves and capturing the reflected signals, GPR systems generate data that can reveal details about underground structures, anomalies, or targets. This capability has proven valuable in tasks ranging from detecting buried utilities and unexploded ordnance to mapping subsurface features in historical sites. However, traditional GPR data analysis is a labor-intensive process requiring significant expertise and interpretive skills, often yielding subjective results dependent on the analyst's experience. By identifying and learning patterns in complex GPR data, ML techniques can facilitate faster and more accurate detection processes, making GPR applications more reliable and accessible across a wider range of fields [1-2].

In recent years, machine learning (ML) has emerged as a powerful approach for processing GPR data, enabling the automation of target detection with reduced human intervention. Machine learning (ML), which has already transformed fields like computer vision, natural language processing, and speech recognition, holds significant potential for improving GPR target detection. Machine learning approaches allow for the extraction of meaningful patterns from complex GPR data, improving both speed and accuracy. The need for an efficient and objective approach to GPR data interpretation has led to growing interest in automated techniques for target detection [3]. This paper reviews existing literature on machine learning-based approaches for automatic target detection in GPR data, discussing the types of features, algorithms, and the main challenges faced in the field.

## 2. BACKGROUND ON GPR AND TARGET DETECTION

### *A. Principles of GPR*

GPR operates by transmitting high-frequency electromagnetic waves into the ground and capturing the reflected signals. The time delay and strength of these reflections are used to map the subsurface environment, with variations indicating the presence of different materials or objects.

### *B. Challenges in Traditional GPR Analysis*

Manual GPR analysis is prone to subjectivity, requires significant expertise, and can be inconsistent due to variations in data quality and environmental conditions. Furthermore, manual interpretation can be time-consuming and inefficient for large datasets.

### *C. Role of Machine Learning in GPR-Based Target Detection*

Machine learning can address many limitations of traditional methods by learning patterns from labelled GPR data, automating target detection, and potentially providing real-time results.

## 3. CHALLENGES IN MACHINE LEARNING FOR GPR TARGET DETECTION

### *A. Data Quality and Environmental Variability*

GPR data quality is affected by environmental factors like soil composition, moisture levels, and temperature. These variations complicate the modeling process and often require adaptive algorithms.

### *B. Limited Annotated Datasets*

Machine learning models generally require large amounts of labeled data, which is scarce for GPR applications. Synthetic data generation and data augmentation techniques are being explored to overcome this limitation.

### *C. Model Generalization*

Models trained on a specific site or set of conditions may not generalize well to different environments. Cross-site generalization remains a major challenge, with ongoing research focusing on domain adaptation and transfer learning.

### *D. Computational Constraints*

Advanced models, particularly deep learning approaches, require significant computational power, limiting their feasibility for real-time and on-field applications.

## 4. LITERATURE REVIEW

Ground Penetrating Radar (GPR) is widely utilized for subsurface exploration and target detection in fields like archaeology, construction, and defense. Advanced processing techniques have been developed to enhance the detection capabilities of GPR data, addressing issues such as noise reduction, resolution enhancement, and feature extraction. Here's a review of some advanced techniques in GPR data processing for improved target detection:

D. Chen et.al. [4] presented a detection method of DCAM-YOLOv5 for ground penetrating radar (GPR) to address the difficulty of identifying complex and multi-type defects in tunnel linings. The diversity of tunnel-lining defects and the multiple reflections and scattering caused by water-bearing defects make GPR images quite complex. Although existing methods can identify the position of underground defects from B-scans, their classification accuracy is not high. The DCAM-YOLOv5 adopts YOLOv5 as the baseline model and integrates deformable convolution and convolutional block attention module (CBAM) without adding many parameters to improve the adaptive learning ability for irregular geometric shapes and boundary fuzzy defects.

Jiangkun Gong et.al. [5] presented a brief examination of Automatic Target Recognition (ATR) technology within ground-based radar systems. It offers a lucid comprehension of the ATR concept, delves into its historical milestones, and categorizes ATR methods according to different scattering regions. By incorporating ATR solutions into radar systems, this study demonstrates the expansion of radar detection ranges and the enhancement of tracking capabilities, leading to superior situational awareness.

F. Hou et.al. [6] developed an automatic method based on a deep instance segmentation framework to detect and segment object signatures from GPR scans. The proposed method develops the Mask Scoring R-CNN (MS R-CNN) architecture by introducing a novel anchoring scheme. By analyzing the characteristics of the hyperbolic signatures of subsurface objects in GPR scans, a set of anchor shape ratios are optimized and selected to substitute the predefined and fixed aspect ratios in the MS R-CNN framework to improve the signature detection performance. In addition, a transfer learning technique is adopted to obtain a pre-trained model to address the challenge of insufficient GPR dataset for model training. The detected and segmented signatures can then be further processed for target localization and characterization. GPR data of tree roots were collected in the field to validate the proposed methods. Despite the noisy background and varying signatures in the GPR scans, the proposed method demonstrated promising results in object detection and segmentation.

Zhongming, Xiang et.al. [7] proposed a rebar recognition method based on the ShearLet Transform, which can distinguish signals from different scales and directions. The proposed method includes two sequential phases: (1) hyperbola decomposition that decomposes rebar signal into a specific scale and direction; and (2) hyperbola reconstruction that reassigns the decomposition components to form new hyperbola without noise. A concrete building is selected to validate our method. The results revealed that: (1) the proposed method can achieve F1 score of 0.9649 on the collected dataset; and (2) it is a robust method that can discriminate strong noise, separate interlaced rebars, and remove cross rebar signals and direct wave.

Donghwi Kim et.al. [8] investigated the effectiveness of data augmentation techniques in the automated analysis of B-scan images from ground-penetrating radar (GPR) using deep learning. Despite the growing interest in automating GPR data analysis and advancements in deep learning for image classification and object detection, many deep learning-based GPR data analysis studies have been limited by the availability of large, diverse GPR datasets. They applied four data augmentation techniques (geometric transformation, color-space transformation, noise injection, and applying kernel filter) to the GPR datasets obtained from a testbed. A deep learning model for GPR data analysis was developed using three models (Faster R-CNN ResNet, SSD ResNet, and EfficientDet) based on transfer learning. It was found that data augmentation significantly enhances model performance across all cases, with the mAP and AR for the Faster R-CNN ResNet model increasing by approximately 4%, achieving a maximum mAP (Intersection over Union = 0.5:1.0) of 87.5% and maximum AR of 90.5%. These results highlight the importance of data augmentation in improving the robustness and accuracy of deep learning models for GPR B-scan analysis.

Yu-Chen Zhang et.al. [9] proposed a method for the automatic corrosive environment detection of bridge decks from ground-penetrating radar (GPR) data based on the single-shot multibox detector (SSD) model. This method can be divided into three steps: data preprocessing, automatic rebar picking, and corrosive environment mapping. First, the GPR data are preprocessed to enhance the contrast of the hyperbolic feature in GPR B-scans. Then the rebars in the B-scan images are automatically picked up by the trained SSD model. Finally, the corrosive environment contour map of the bridge deck is generated with the rebar reflection amplitudes after depth correction. The SSD model was trained with 10,316 B-scan images and tested with 2,578 images. The 300×300-pixel B-scan image typically included three to five hyperbolas. A case study with GPR data from a tested bridge was employed to validate the feasibility of the proposed method. The results show that the accuracy of the automatic corrosive environment detection method can reach 98% and is considerably higher than that of commercial software methods.

Leila Carolina Martoni Amaral et.al. [10] presented the application of the state-of-the-art You Only Look Once (YOLO) v5 algorithm to detect underground objects using GPR images. A GPR dataset was prepared by collecting GPR images in a laboratory setup. For this purpose, a commercially available 2GHz high-frequency GPR antenna was used, and a dataset was collected with images of metal and PVC pipes, air and water voids, and boulders. The YOLOv5 algorithm was trained with a dataset that successfully detected and classified underground objects to their respective classes.

Yi-Tao Dou et.al. [11] combined ground penetrating radar (GPR) and convolutional neural networks for the intelligent detection of underground road targets. The target location was realized using a gradient-class activation map (Grad-CAM). First, GPR technology was used to detect roads and obtain radar images. This study constructs a radar image dataset containing 3000 underground road radar targets, such as underground pipelines and holes. Based on the dataset, a ResNet50 network was used to classify and train different underground targets. During training, the accuracy of the training set gradually increases and finally fluctuates approximately 85%. The loss function gradually decreases and falls between 0.2 and 0.3. Finally, targets were located using Grad-CAM. The positioning results of single and multiple targets are consistent with the actual position, indicating that the method can effectively realize the intelligent detection of underground targets in GPR.

Hai Liu et.al. [12] proposed an automatic GPR method for recognition and localization of underground pipelines based on a deep learning model in the paper. Firstly, a dataset containing 3,824 real GPR B-scans of pipelines is established. Secondly, a You Only Look Once version 3 (YOLOv3) model is trained to recognize the regions of the underground pipelines in a GPR image. Thirdly, the hyperbolic response of a pipeline is focused by migration, and transformed into a binary image by an iterative thresholding method. Finally, the apex of the hyperbola is employed to estimate both the horizontal position and the buried depth of the pipeline. Field experiments validated that the absolute errors of the estimated depths are less than 0.04 m and the average relative error is lower than 4 %.

Kehui Chen et.al. [13] proposed a novel recognition method based on time-frequency texture features and a support vector machine (SVM). The proposed method first extracts texture features from the gray co-occurrence matrix of S transform time-frequency images for the A-scan data, then establishes the SVM model and realizes the target recognition. The proposed method is assessed using synthetic GPR images and compared with the other two time-frequency analysis methods, combined with SVM. The experimental results show that the proposed method can achieve higher recognition accuracies than the other two methods in a heavily noisy environment.

Mohd Shuhanaz Zanar Azalan et.al. [14] proposed a framework to classify the size of underground metallic pipe by using Histogram of Oriented Gradient (HOG) as a feature extraction algorithm. Two machine learning algorithms, Support Vector Machines (SVM) and Backpropagation Neural Network, were proposed to classify the size of the underground metallic pipe. As a result, the accuracy from the identification is more than 98% for both classifier algorithm.

Man-Sung Kang et.al. [15] proposed a system based on deep convolutional neural networks, which is capable of autonomous underground cavity detection beneath urban roads using three-dimensional ground penetrating radar data. First, a basis pursuit-based background filtering algorithm is developed to enhance the visibility of underground objects. The deep convolutional neural network is then established and applied to automatically classify underground objects using the filtered three-dimensional ground penetrating radar data as represented by three types of images: A-, B-, and C-scans. They utilize a novel two-dimensional grid image consisting of several B- and C-scan images. Cavity, pipe, manhole, and intact features extracted from in situ three-dimensional ground penetrating radar data are used to train the convolutional neural network.

Daffa Dewantara et.al. [16] proposed a new method for automating hyperbola detection and apex extraction on radargram. The model consists of two modules that take radargram as input in a form of images. In the first module, we used the Faster-RCNN to extract the hyperbola segments as a set of rectangular boundary boxes. The network was trained using synthetic radargram data simulated by the gprMax software. The second module is to estimate the coordinates of the hyperbola apex using an image processing technique. We had correctly detected all hyperbola on the simulated radargram from the test set. For the test on field radargram, the framework is capable of processing radargram that is similar to the simulated radargram data. The problem with the second module occurs on interference hyperbola as the searching window is disturbed by the noise. Apart from those problems, by using these two modules, the detection of buried cylindrical objects using GPR can be automated with a minimal amount of time.

Changle Xin et.al. [17] proposed a method that can achieve fast goals in complex multi-goal situations. The simplified ResNet-50 network is used to detect dense intersecting hyperbolic curves and reduce the computation of the network. At the same time, we use k-means clustering algorithm to optimize the anchor in faster-Rcnn based on the characteristics of GPR hyperbola. In addition, this method is also suitable for target detection on GPR images under random media.

H. Harkat et.al. [18] proposed an alternative classification methodology. The goal is to classify windows of GPR radargrams into two classes (with or without target) using a neural network radial basis function (RBF), designed via a multi-objective genetic algorithm (MOGA). To capture samples' fine details, high order statistic cumulant features (HOS) were used. Feature selection was performed by MOGA, with an optional prior reduction using a mutual information (MIFS) approach. The obtained results demonstrate improvement of the classification performance when compared with other models designed with the same data and are among the best results available in the literature, albeit the large reduction in classifier complexity.

Zhi Qiu et.al. [19] combined GPR and intelligent technology to conduct research on three aspects: acquiring real-time GPR images, using the YOLOv5 algorithm for real-time target detection and the coordinate positioning of GPR images, and the construction of a detection system based on ground-penetrating radar and the YOLOv5 algorithm that automatically detects target characteristic curves in ground-penetrating radar images. In addition, taking five groups of test results of detecting different diameters of rebar inside the soil as an example, the obtained average error of detecting the depth of rebar using the detection system is within 0.02 m, and the error of detecting rebar along the measuring line direction from the location of the starting point of GPR detection is within 0.08 m. The experimental results show that the detection system is important for identifying and positioning foreign objects inside the soil.

Zhimin Gong et.al. [20] proposed a deep-learning based Faster R-CNN algorithm for the automatic classification and recognition of GPR images. Firstly, GPR images with different features were obtained by using gprMax, a professional GPR simulation software. Then, the feature of the target in the image was taken as the recognition object, and the data set was made. Finally, Faster R-CNN's recognition ability of GPR images was analysed from various accuracy, average accuracy and other indicators. The results showed that Faster R-CNN could successfully identify GPR images and accurately classify them, with an average accuracy rate of 93.9%.

Guangyan Cui et.al. [21] proposed the accurate calculation of electromagnetic wave velocity (AC-EWV) by searching for the minimum image entropy of migrated radargrams. To avoid global searching, potential positions of object hyperbolas are selected from the binarized radargram through the vertical gray gradient searching, then the sub_window is extracted with the potential position as the center. The best fitting hyperbola is detected with the genetic algorithm (GA) in the sub_window, and objects are finally determined with five hyperbolic matching criteria and the auto-categorization. This technique is verified with the simulated and measured GPR data about rebars, pipelines, and voids, and results demonstrate that it achieves the average correct rate, average missed rate, and the average misjudged rate is 98.46%, 1.33%, and 0.36%, respectively, and the average correct rate for GPR data of the double-layer rebars is 91.67%.

Volodymyr Motyka et.al. [22] built a target recognition model in the form of AGM-86C (CALCM) and CR Taurus KEPD 350 cruise missiles. A module for recognizing AGM-86C and Taurus KEPD 350 cruise missiles has also been built, which sufficiently accurately recognizes these types of missiles (accuracy - 84.52%). Because one of the missiles is sometimes referred to as a missile developed using "stealth" technology, the model can be considered effective. The disadvantage of the model is that the model is trained on only two types of missiles. The problem is that the data on the effective scattering surface of all missiles in any state's arsenal is top-secret data.

Yunjie Zhong et.al. [23] presented a technique in which the ground-penetrating radar echo images (B-scan) after processing are mean-filtered to eliminate the direct waves that interfere greatly with the echoes. The RFB-s structure is added to the YOLOv3-SPP network structure, while the Anchor value is optimized and the EIOU loss function is introduced. For four types of data with different shapes and properties at random target locations, three models, YOLOv3, YOLOv3-SPP, and the improved YOLOv3-SPP, are used for classification and identification, and the proposed algorithm models are comprehensively evaluated using model evaluation metrics. The experimental results show that the algorithm models proposed in this paper have a good recognition effect in ground-penetrating radar echo image target detection.

Wei Xue et.al. [24] proposed an efficient underground target detection method for urban roads based on neural networks. First, robust principal component analysis (RPCA) is used to suppress the clutter in the B-scan image. Then, three time-domain statistics of each A-scan signal are calculated as its features, and one backpropagation (BP) neural network is adopted to recognize A-scan signals to obtain the horizontal regions of targets. Next, the fusion and deletion (FAD) algorithm is used to further optimize the horizontal regions of targets. Finally, three time-domain statistics of each segmented A-scan signal in the horizontal regions of targets are extracted as the features, and another BP neural network is employed to recognize the segmented A-scan signals to obtain the vertical regions of targets. The proposed method is verified with both simulation and real GPR data. The experimental results show that the proposed method can effectively locate the horizontal ranges and vertical depths of underground targets for urban roads and has higher recognition accuracy and less processing time than the traditional segmentation recognition methods.

Junyi Zou et.al. [25] proposed a real-time target detection system based on the multi-source fusion method. Based on the ROS melodic software development environment and the NVIDIA Xavier hardware development platform, this system integrates sensing devices such as millimeter-wave radar and camera, and it can realize functions such as real-time target detection and tracking. At first, the image data can be processed by the You Only Look Once v5 network, which can increase the speed and accuracy of identification; secondly, the millimeter-wave radar data are processed to provide a more accurate distance and velocity of the targets. Meanwhile, to improve the accuracy of the system, the sensor fusion method is used. The radar point cloud is projected onto the image, then through space-time synchronization, region of interest (ROI) identification, and data association, the target-tracking information is presented. At last, field tests of the system are conducted, the results of which indicate that the system has a more accurate recognition effect and scene adaptation ability in complex scenes.

## 5. CONCLUSION

Machine learning techniques offer promising solutions for automating target detection in GPR data, providing increased accuracy and efficiency over traditional methods. Advanced feature extraction, classification algorithms, and deep learning approaches have shown significant potential in improving detection accuracy. However, challenges such as data variability, computational constraints, and limited labeled datasets continue to pose obstacles. Future research should focus on addressing these challenges to develop more robust and generalizable machine learning-based GPR target detection systems. Integrating these advancements will lead to more efficient and reliable applications of GPR in various fields, ultimately contributing to safer and more effective subsurface exploration.

## REFERENCES

1. Rangole, Abhishek & de, Sampurna & Kuchekar, Nilesh & Raj, Arockia. (2024). A Comprehensive Review of Ground Penetrating Radar: Techniques, Applications and Future Directions. 12. 30-53. http://dx.doi.org/10.5281/zenodo.13842586.
2. Nansha Li, Haifeng Li and Renbiao Wu, "Ground Penetrating Radar Based Subsurface Object Detection: Mini Review", COJ Robotics & Artificial Intelligence, http://dx.doi.org/10.31031/cojra.2021.01.000515.
3. Sui, Xin & Leng, Zhen & Wang, Siqi. (2023). "Machine learning based detection of transportation infrastructure internal defects using ground penetrating radar: a state-of-the-art review". Intelligent Transportation Infrastructure. 2. http://dx.doi.org/10.1093/iti/liad004.
4. Chen, D. & Xiong, S. & Guo, L.. (2023). Research on Detection Method for Tunnel Lining Defects Based on DCAM-YOLOv5 in GPR B-Scan. Radioengineering. 32. 299-311. http://dx.doi.org/10.13164/re.2023.0299.
5. Gong, Jiangkun, et al. "An Introduction to Radar Automatic Target Recognition (ATR) Technology in Ground-based Radar Systems." ArXiv,2023, https://arxiv.org/abs/2310.14769.
6. F. Hou, W. Lei, S. Li and J. Xi, "Deep Learning-Based Subsurface Target Detection From GPR Scans," in IEEE Sensors Journal, vol. 21, no. 6, pp. 8161-8171, 15 March15, 2021, http://dx.doi.org/10.1109/JSEN.2021.3050262
7. Xiang, Zhongming & Ou, Ge & Rashidi, Abbas & Hassandokht Mashhadi, Ali. (2022). "A Shearlet Transform-Based Method for Automated Rebar Recognition Using GPR B-Scan Image Data". 30-39. 10.1061/9780784483961.004.
8. Donghwi Kim, Jihoon Kim and Heejung Youn, "Automated ground penetrating radar B-scan detection enhanced by data augmentation techniques", Geomechanics and Engineering, Volume 38, Number 1, July10 2024,pages 29-44. DOI: https://doi.org/10.12989/gae.2024.38.1.029.
9. Yu-Chen Zhang, S.M.ASCE, Ting-Hua Yi, M.ASCE, Shibin Lin, A.M.ASCE, Hong-Nan Li, F.ASCE, and Songtao Lv, M.ASCE, "Automatic Corrosive Environment Detection of RC Bridge Decks from Ground-Penetrating Radar Data Based on Deep Learning", Journal of Performance of Constructed Facilities, 2022, Volume 36, Issue 2, https://doi.org/10.1061/(ASCE)CF.1943-5509.0001712.
10. Leila Carolina Martoni Amaral martonia, Aditya Roshan, and Alireza Bayat, "Automatic Detection and Classification of Underground Objects in Ground Penetrating Radar Images Using Machine Learning", Journal of Pipeline Systems Engineering and Practice, 2023, Volume 14, Issue 4, https://doi.org/10.1061/JPSEA2.PSENG-1444.
11. Dou, YT., Dong, GQ. & Li, X. "Automatic identification of GPR targets on roads based on CNN and Grad-CAM. Appl". Geophys. (2024). https://doi.org/10.1007/s11770-024-1105-8.
12. Liu, Hai, et al. "Automatic Recognition and Localization of Underground Pipelines in GPR B-scans Using a Deep Learning Model." Tunnelling and Underground Space Technology, vol. 134, 2023, p. 104861, https://doi.org/10.1016/j.tust.2022.104861.
13. K. Chen, W. Xue, Z. Wang and S. Ma, "Automatic Target Recognition in GPR Images Based on Time-Frequency Texture Features and Support Vector Machine," 2021 China Automation Congress (CAC), Beijing, China, 2021, pp. 2876-2881, doi: 10.1109/CAC53003.2021.9727358.
14. Mohd Shuhanaz Zanar Azalan et al "Classification Size of Underground Object from Ground Penetrating Radar Image using Machine Learning Technique," 2023 J. Phys.: Conf. Ser. 2550 012029. DOI 10.1088/1742-6596/2550/1/012029.
15. Kang, Man-Sung & Kim, Namgyu & Lee, Jong Jae & An, Yun-Kyu. (2019). "Deep learning-based automated underground cavity detection using three-dimensional ground penetrating radar Structural Health Monitoring". 19. 147592171983808. 10.1177/1475921719838081.
16. D. Dewantara and W. W. Parnadi, "Automatic hyperbola detection and apex extraction using convolutional neural network on GPR data," Journal of Physics Conference Series, vol. 2243, no. 1, p. 012027, Jun. 2022, doi: https://doi.org/10.1088/1742-6596/2243/1/012027.
17. C. Xin, W. Lei, C. Luo and W. Xue, "Ground penetrating radar target detection method based on optimized faster RCNN and k-means clustering," IET International Radar Conference (IRC 2023), Chongqing, China, 2023, pp. 70-73, doi: 10.1049/icp.2024.1053.
18. Harkat, H., et al. "GPR Target Detection Using a Neural Network Classifier Designed by a Multi-objective Genetic Algorithm." Applied Soft Computing, vol. 79, 2019, pp. 310-325, https://doi.org/10.1016/j.asoc.2019.03.030.
19. Qiu, Zhi, et al. "Research on Real-Time Automatic Picking of Ground-Penetrating Radar Image Features by Using Machine Learning." Horticulturae, vol. 8, no. 12, 2022, p.1116,https://doi.org/10.3390/horticulturae8121116.
20. Z. Gong and H. Zhang, "Research on GPR image recognition based on deep learning," MATEC Web of Conferences, vol. 309, p. 03027,Jan.2020,doi:https://doi.org/10.1051/matecconf/2020309 03027.
21. G. Cui, J. Xu, Y. Wang and S. Zhao, "Multiple Objects Automatic Detection of GPR Data Based on the AC-EWV and Genetic Algorithm," in IEEE Transactions on Geoscience and Remote Sensing, vol. 61, pp. 1-16, 2023, Art no. 5100516, doi: https://doi.org/10.1109/TGRS.2022.3228571.
22. Volodymyr Motyka et.al., "Radar Target Recognition Based on Machine Learning", IntelITSIS'2023: 4th International Workshop on Intelligent Information Technologies and Systems of Information Security, March 22–24, 2023, Khmelnytskyi, Ukraine.
23. Y. Zhong, K. Li, S. Mo, and X. Liu, "GPR Target Recognition Based on Improved YOLOv3-SPP," Preprints.org; 2023. DOI: https://doi.org/10.20944/preprints202305.1363.v1Xue, Wei, et al. "Efficient Underground Target Detection of Urban Roads in Ground-Penetrating Radar Images Based on Neural Networks." Remote Sensing, vol. 15, no. 5, 2022,p.1346,https://doi.org/10.3390/rs15051346.

24. Zou, Junyi, et al. "Real-Time Target Detection System for Intelligent Vehicles Based on Multi-Source Data Fusion." Sensors, vol. 23, no.4,2022,p.1823,https://doi.org/10.3390/s23041823.

## BIOGRAPHIES

Gaurav R. Savade, has received the B.E. Electronics and Tele-communication from Sant Gadge Baba Amravati university, Amravati 2008. He is currently doing M.E. in Digital Electronics from Babasaheb Naik College of Engg., Pusad from Sant Gadge Baba, Amravati University, Amravati. He worked as an Assistant Professor at Babasaheb Naik College Of Engineering, Pusad. His research interests include digital image processing, VLSI circuits and Embedded system design.