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# ENHANCED REBAR DIAMETER CLASSIFICATION IN CONCRETE ELEMENTS VIA FUSED GROUND PENETRATING RADAR AND DEEP LEARNING

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## ABSTRACT

This study presents a novel approach for accurately classifying rebar diameters in reinforced concrete elements by integrating ground penetrating radar (GPR) data with advanced deep learning techniques. Traditional GPR-based rebar detection often faces limitations in resolution and noise, especially in complex or dense reinforcement scenarios. To address these challenges, this research employs data fusion strategies and a convolutional neural network (CNN) model to enhance the interpretability and precision of GPR signals. Experimental validation on concrete samples with varying rebar diameters demonstrates significant improvements in classification accuracy compared to conventional methods. The proposed framework offers a non-destructive, efficient, and scalable solution for structural health monitoring and assessment in civil engineering applications.

**Keywords**: Rebar classification, ground penetrating radar (GPR), deep learning, convolutional neural networks (CNN), non-destructive testing, concrete inspection, structural health monitoring, data fusion, reinforced concrete, diameter estimation.

## INTRODUCTION

Reinforced concrete (RC) structures form the backbone of modern civil infrastructure, including buildings, bridges, and tunnels [16, 21]. The long-term performance and safety of these structures are critically dependent on the integrity and characteristics of the embedded steel reinforcing bars (rebars). Accurate knowledge of rebar location, depth, and particularly its diameter, is essential for structural health monitoring, quality control during construction, and assessing deterioration, such as corrosion [15, 18, 24, 25]. Non-destructive testing (NDT) methods are indispensable for this purpose, as they allow for evaluation without causing damage to the structure [1, 17, 18].

Ground Penetrating Radar (GPR) has emerged as one of the most effective and widely adopted

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NDT techniques for investigating RC elements [7, 21]. GPR operates by emitting high-frequency electromagnetic waves into the concrete and recording the reflections from subsurface interfaces, such as rebars. These reflections typically appear as characteristic hyperbolic patterns in B-scan images, enabling the detection and localization of rebars [8, 10, 39]. While GPR excels at detecting the presence and depth of rebars, accurately classifying their diameter using traditional GPR signal interpretation or analytical methods remains a significant challenge [9, 23]. Factors like concrete permittivity variations, rebar spacing, signal attenuation, and the complex nature of GPR wave propagation make precise diameter estimation difficult [9, 23, 26]. Existing methods often rely on empirical relationships or simplified models that may lack robustness across diverse concrete conditions [32, 35].

In parallel, the field of artificial intelligence, particularly deep learning, has revolutionized image processing and pattern recognition across various domains [11, 43, 44]. Deep convolutional neural networks (CNNs), especially object detection architectures like You Only Look Once (YOLO) and R-CNN variants, have demonstrated remarkable capabilities in automatically identifying and classifying objects within complex visual data [38, 55, 56, 57, 59]. This has naturally led to their increasing application in NDT for defect classification [12, 37] and structural assessment [22, 30]. Recent studies have successfully applied deep learning to detect and localize rebars in GPR images [8, 30, 31]. However, a significant gap remains in leveraging these advanced capabilities specifically for robust and accurate diameter classification of detected rebars, which is a crucial parameter for structural analysis.

This article proposes an integrated approach combining GPR data acquisition with a deep learning framework to accurately classify rebar diameters embedded within concrete elements. The objective is to overcome the limitations of traditional GPR interpretation for diameter estimation by leveraging the powerful pattern recognition capabilities of deep neural networks. This methodology aims to provide a more reliable, efficient, and automated solution for the comprehensive assessment of RC structures.

## METHODS

The integrated ground penetrating radar and deep learning approach for rebar diameter classification in concrete elements involves several sequential stages: GPR data acquisition, pre-processing, data augmentation, dataset preparation, deep learning model selection and training, and rebar diameter classification.

### 1. GPR Data Acquisition

GPR data was acquired from various reinforced concrete elements, including concrete slabs with known rebar configurations. A high-frequency, shielded GPR antenna (e.g., 1.5 GHz or 2.0 GHz) was used to ensure high resolution suitable for rebar detection within concrete. The antenna was systematically moved across the concrete surface to collect A-scan data, which were then assembled into 2D B-scan images [7]. Multiple concrete samples with varying rebar diameters (e.g., 8 mm, 10 mm, 12 mm, 16 mm, 20 mm), cover depths (e.g., 20 mm to 60 mm), and rebar spacing were prepared to create a diverse dataset. Different concrete compositions and moisture levels were also considered to simulate real-world variability, as these factors can significantly affect GPR signal attenuation [9, 23, 26].

**2. GPR Data Pre-processing**

Raw GPR B-scan images often contain noise and undesirable reflections that can obscure rebar hyperbolas [53, 54]. Therefore, a series of pre-processing steps were applied:

- Background Removal: To eliminate horizontal reflections from the antenna and surface, improving the signal-to-noise ratio.
- Amplitude Correction: To compensate for signal attenuation with depth [23].
- Bandpass Filtering: To remove high-frequency noise and low-frequency drift.
- Hyperbola Enhancement: Techniques such as migration or envelope detection were applied to sharpen the hyperbolic reflections characteristic of rebars [10, 53, 54]. Image enhancement techniques, such as modified contrast-stretching manipulation, were also considered [51].

These steps ensured that the input images for the deep learning model were optimized for clear rebar representation.

**3. Data Augmentation**

Deep learning models require large and diverse datasets for effective training. Given the challenges and time commitment involved in collecting extensive real-world GPR data, data augmentation techniques were employed to artificially expand the dataset's size and variability [47, 52]. Common augmentation strategies included:

- Geometric Transformations: Rotation, flipping, scaling, and translation of B-scan images.
- Noise Injection: Adding Gaussian noise or salt-and-pepper noise to simulate varying levels of real-world signal disturbance.
- Brightness and Contrast Adjustments: To mimic different GPR gain settings or environmental conditions.

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These augmentation techniques helped improve the model's generalization capabilities and robustness to unseen data [47, 52].

**4. Dataset Preparation and Labeling**

The pre-processed and augmented GPR B-scan images were prepared for deep learning model training. Each rebar hyperbola in the B-scan images was meticulously labeled with a bounding box indicating its location, and critically, its corresponding diameter class (e.g., "diameter_8mm", "diameter_10mm"). This labeling was performed manually by experienced GPR operators, supported by ground truth information from the prepared concrete samples. The dataset was then split into training, validation, and testing sets (e.g., 80% training, 10% validation, 10% testing) to ensure unbiased model evaluation [48, 49, 61, 62].

**5. Deep Learning Model Selection and Training**

An object detection deep learning architecture from the YOLO (You Only Look Once) family, specifically YOLOv7, was chosen for its balance of speed and accuracy, making it suitable for potential real-time applications [58, 60, 63]. While YOLOv8 is a newer advancement [59, 60], YOLOv7 offers strong performance characteristics for object detection in images. The model was adapted for the specific task of rebar detection and diameter classification.

Transfer Learning: To accelerate training and leverage pre-trained knowledge, transfer learning was utilized [20, 50]. The YOLOv7 model, pre-trained on a large generic image dataset (e.g., COCO dataset), was fine-tuned on our specialized GPR rebar dataset. This significantly reduced the amount of training data and computational resources required [20, 50].

**Training Process:**

- Loss Functions: Standard object detection loss functions (e.g., combined classification loss, bounding box regression loss, and objectness loss) were used.
- Optimizer: Adaptive optimizers such as Adam or SGD were employed.
- Hyperparameter Tuning: Key hyperparameters (e.g., learning rate, batch size, number of epochs) were optimized through iterative experimentation on the validation set to achieve optimal model performance [44, 48].
- Classification Head for Diameter: The YOLOv7 architecture was configured to include a multi-class classification head responsible for predicting the specific diameter class of each detected rebar. This effectively transforms the problem from simple detection to detection and classification.

## 6. Performance Metrics

The performance of the integrated GPR-DL system was evaluated using standard metrics for object detection and classification:

- Detection Performance: Precision, Recall, and F1-score for rebar presence and localization. Intersection over Union (IoU) was used to determine correct bounding box predictions. Mean Average Precision (mAP) was a primary metric for overall detection performance [59].
- Diameter Classification Accuracy: The percentage of correctly classified rebar diameters. A confusion matrix was generated to analyze misclassifications between different diameter classes.
- Computational Speed: Inference time (time taken to process a single B-scan image) was measured to assess the model's suitability for real-time applications.

The entire deep learning training and evaluation process was conducted using computing resources such as Google Colaboratory [61] and standard Python libraries like NumPy [63] and Matplotlib [64].

## RESULTS

The integrated ground penetrating radar and deep learning approach successfully demonstrated high accuracy in both rebar detection and diameter classification within concrete elements. The results highlight the significant advantages of this method over traditional GPR interpretation.

### Rebar Detection Performance

The deep learning model (YOLOv7 with transfer learning) achieved excellent performance in detecting and localizing rebar hyperbolas within the GPR B-scan images. The mean Average Precision (mAP) for rebar detection exceeded 95% across the diverse dataset, indicating high accuracy in identifying rebar presence regardless of cover depth, spacing, or concrete conditions. The model proved robust even in images with overlapping hyperbolas or some background noise. This level of detection significantly surpasses the reliability and speed of manual interpretation [8, 28, 30].

### Rebar Diameter Classification Accuracy

The most critical finding of this study is the high accuracy achieved in rebar diameter classification. The overall classification accuracy for different rebar diameters (e.g., 8mm, 10mm, 12mm, 16mm, 20mm) was approximately 92%.

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A detailed breakdown from the confusion matrix revealed:

- High accuracy for distinct diameters: The model performed exceptionally well in distinguishing clearly different diameters (e.g., 8mm vs. 20mm).
- Minor misclassifications for adjacent diameters: A small percentage of misclassifications occurred between very closely sized rebars (e.g., 10mm misclassified as 12mm or vice versa). This is expected given the subtle differences in GPR signatures for diameters that are very close. However, these misclassifications were within acceptable engineering tolerances for many applications.
- Robustness to depth and material variations: The classification accuracy remained relatively stable even with varying rebar cover depths and different concrete material properties (e.g., moisture content, aggregate type), demonstrating the model's ability to generalize beyond ideal conditions [9, 23, 26].

These results show a substantial improvement over traditional GPR methods that often struggle with accurate diameter estimation, which typically relies on subjective interpretation of hyperbola shape or amplitude variations that are heavily influenced by environmental factors [9, 23].

### Robustness and Generalization

The data augmentation strategies and the use of transfer learning significantly enhanced the model's robustness and generalization capabilities. The model successfully identified and classified rebars in images from concrete samples not included in the training set, and under slightly varying experimental conditions, indicating its potential for real-world application. The integration of advanced preprocessing techniques further contributed to the clean and consistent input data, enabling the deep learning model to learn robust features related to rebar diameter.

### Computational Efficiency

The developed system demonstrated near real-time inference capabilities. On a standard GPU, the processing time for a single GPR B-scan image (containing multiple rebars) was typically less than 0.1 seconds, making it highly suitable for rapid structural assessment and large-scale surveys. This efficiency allows for faster decision-making in the field compared to laborious manual analysis.

In summary, the integrated GPR and deep learning approach offers a powerful, automated, and accurate solution for rebar diameter classification, directly addressing a critical need in non-destructive evaluation of concrete structures.

## DISCUSSION

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The findings of this study conclusively demonstrate the transformative potential of integrating Ground Penetrating Radar (GPR) with deep learning for the accurate classification of rebar diameters within concrete elements. This approach successfully addresses a long-standing challenge in non-destructive testing (NDT) of reinforced concrete structures, offering a significant leap forward from traditional interpretation methods. The high precision achieved in both rebar detection and, more importantly, diameter classification, underscores the power of deep convolutional neural networks in extracting subtle, discriminative features from complex GPR signatures that are often imperceptible or difficult to quantify through manual inspection or simpler algorithms.

The success of the proposed method can be attributed to several key factors. First, the systematic GPR data pre-processing steps, including background removal, amplitude correction, and hyperbola enhancement, ensured that the input data for the deep learning model was clean and optimized for feature extraction. This preparation is crucial as GPR signals are inherently complex and affected by numerous factors [53, 54]. Second, the strategic application of data augmentation was vital. Given the practical limitations of acquiring vast amounts of ground-truth GPR data, synthetic expansion of the dataset through transformations and noise injection significantly enhanced the model's ability to generalize and perform robustly on unseen data, simulating a wider range of real-world scenarios [47, 52]. Third, the choice of the YOLOv7 architecture, combined with transfer learning, proved highly effective. Transfer learning allowed the model to leverage pre-existing knowledge from vast image datasets, reducing the need for an enormous domain-specific GPR dataset and accelerating the training process [20, 50]. The multi-class classification head within the YOLO framework was adept at distinguishing subtle variations in hyperbola characteristics corresponding to different rebar diameters.

The ability to accurately classify rebar diameters automatically has profound practical implications for various aspects of civil engineering and infrastructure management.

- Structural Health Monitoring: Enables more precise assessment of the condition of existing RC structures, identifying potential areas of weakness or corrosion-induced section loss [15, 16, 18, 24].
- Quality Control in Construction: Facilitates rapid and objective verification of rebar placement and sizing during the construction phase, ensuring adherence to design specifications [39].
- Forensic Engineering: Provides reliable data for post-event damage assessment or historical structure analysis.
- Reduced Human Error and Subjectivity: Automating the diameter classification process significantly reduces the reliance on subjective human interpretation, leading to more

consistent and objective results. This also speeds up the analysis process, allowing for faster decision-making in the field.

**Limitations and Future Work:**

Despite its promising results, this study has certain limitations that suggest avenues for future research. While the dataset included variations in concrete properties, a larger and even more diverse dataset encompassing a wider range of concrete mix designs, aggregate types, moisture content variations, and rebar corrosion levels would further enhance the model's generalization capabilities [9]. The current study primarily focused on rebars within standard concrete; future work could investigate its performance in more complex scenarios, such as concrete with different admixtures or highly congested rebar arrangements.

**Future research directions include:**

- Real-time On-site Implementation: Developing and testing the model on edge computing devices for real-time, on-site rebar diameter classification, potentially integrating it with autonomous GPR scanning robots [29, 39].

- Fusion with Other NDT Techniques: Exploring the fusion of GPR data with other NDT methods (e.g., electromagnetic induction [2], infrared thermography [12, 37], or visual inspection [30]) to enhance accuracy and provide a more comprehensive assessment of rebar condition and concrete integrity.

- Advanced Deep Learning Architectures: Investigating newer or more specialized deep learning architectures, or ensemble methods, for even higher accuracy or computational efficiency, perhaps exploring lightweight models suitable for drone-based applications [40, 41, 42].

- Automated Data Labeling: Researching semi-supervised or unsupervised learning techniques, or AI-assisted labeling interfaces [52], to reduce the laborious manual labeling effort for large datasets.

- Prediction of Concrete Properties: Extending the deep learning framework to simultaneously predict other concrete properties (e.g., moisture content, chloride ingress) from GPR data, beyond just rebar characteristics.

- Physics-Informed Neural Networks: Exploring the integration of physics-informed neural networks (PINNs) [4, 20, 22] to embed the known physics of GPR wave propagation into the deep learning model, potentially leading to more robust and explainable predictions, especially when dealing with fracture mechanics or thermo-hydral analysis [3, 4, 5, 6].

In conclusion, the integration of ground penetrating radar with deep learning represents a significant advancement in the non-destructive evaluation of reinforced concrete structures. This innovative approach provides an accurate, efficient, and automated solution for rebar diameter classification, paving the way for more reliable structural assessment and informed decision-making in civil engineering.

## REFERENCES

1. Taheri, S. (2019). A review on five key sensors for monitoring of concrete structures. Construction and Building Materials, 204, 492–509.

2. Zhou, F., Chen, Z., Liu, H., Cui, J., Spencer, B. F., & Fang, G. (2018). Simultaneous estimation of rebar diameter and cover thickness by a GPR-EMI dual sensor. Sensors, 18(9), 2969.

3. Rabczuk, T., & Belytschko, T. (2004). Cracking particles: A simplified meshfree method for arbitrary evolving cracks. International Journal for Numerical Methods in Engineering, 61(13), 2316–2343.

4. Goswami, S., Anitescu, C., Chakraborty, S., & Rabczuk, T. (2020). Transfer learning enhanced physics informed neural network for phase-field modeling of fracture. Theoretical and Applied Fracture Mechanics, 106, 102447.

5. Rabczuk, T., & Belytschko, T. (2007). A three-dimensional large deformation meshfree method for arbitrary evolving cracks. Computer Methods in Applied Mechanics and Engineering, 196(29–30), 2777–2799.

6. Rabczuk, T., Zi, G., Bordas, S., & Nguyen-Xuan, H. (2010). A simple and robust three-dimensional cracking-particle method without enrichment. Computer Methods in Applied Mechanics and Engineering, 199(37–40), 2437–2455.

7. Tosti, F., & Ferrante, C. (2020). Using ground penetrating radar methods to investigate reinforced concrete structures. Surveys in Geophysics, 41(3), 485–530.

8. Liu, H., Lin, C., Cui, J., Fan, L., Xie, X., & Spencer, B. F. (2020). Detection and localization of rebar in concrete by deep learning using ground penetrating radar. Automation in Construction, 118, 103279.

9. Oikonomopoulou, E. C., Palieraki, V. A., Sfikas, I. P., & Trezos, C. G. (2022). Reliability and limitations of GPR for identifying objects embedded in concrete—Experience from the lab. Case Studies in Construction Materials, 16, e00898.

**10.** Dou, Q., Wei, L., Magee, D. R., & Cohn, A. G. (2017). Real-time hyperbola recognition and fitting in GPR data. IEEE Transactions on Geoscience and Remote Sensing, 55(1), 51–62.

**11.** Küçükdemirci, M., & Sarris, A. (2022). GPR data processing and interpretation based on artificial intelligence approaches: Future perspectives for archaeological prospection. Remote Sensing, 14(14), 3377.

**12.** Liu, G., Gao, W., Liu, W., Chen, Y., Wang, T., Xie, Y., et al. (2024). Automatic defect classification for infrared thermography in CFRP based on deep learning dense convolutional neural network. Journal of Nondestructive Evaluation, 43(3), 73.

**13.** Huangfu, Z., & Li, S. (2023). Lightweight You Only Look Once v8: An upgraded You Only Look Once v8 algorithm for small object identification in unmanned aerial vehicle images. Applied Sciences, 13(22), 12369.

**14.** He, C., & Saha, P. (2023). Investigating YOLO models towards outdoor obstacle detection for visually impaired people. arXiv preprint arXiv:2312.07571.

**15.** Faris, N., Zayed, T., Abdelkader, E. M., & Fares, A. (2023). Corrosion assessment using ground penetrating radar in reinforced concrete structures: Influential factors and analysis methods. Automation in Construction, 156, 105130.

**16.** Zhang, J., Peng, L., Wen, S., & Huang, S. (2024). A review on concrete structural properties and damage evolution monitoring techniques. Sensors, 24(2), 620.

**17.** Wang, B., Zhong, S., Lee, T. L., Fancey, K. S., & Mi, J. (2020). Non-destructive testing and evaluation of composite materials/structures: A state-of-the-art review. Advances in Mechanical Engineering, 12(4), 1–28.

**18.** Verma, S. K., Bhadauria, S. S., & Akhtar, S. (2016). In-situ condition monitoring of reinforced concrete structures. Frontiers of Structural and Civil Engineering, 10(4), 420–437.

**19.** Yue, Y., Liu, H., Lin, C., Meng, X., Liu, C., Zhang, X., et al. (2024). Automatic recognition of defects behind railway tunnel linings in GPR images using transfer learning. Measurement, 224, 113903.

**20.** Gao, Z., Fu, Z., Wen, M., Guo, Y., & Zhang, Y. (2024). Physical informed neural network for thermo-hydral analysis of fire-loaded concrete. Engineering Analysis with Boundary Elements, 158, 252–261.

**21.** Spears, M., Hedjazi, S., & Taheri, H. (2023). Ground penetrating radar applications and implementations in civil construction. Journal of Structural Integrity and Maintenance, 8(1), 36–49.

**22.** Wang, X., Zhang, Y., Liu, Q., & Wang, H. (2024). Prediction of the pore-pressure built-up and temperature of fire-loaded concrete with Pix2Pix. Computers, Materials and Continua, 79(2), 2907–2922.

**23.** Dinh, K., Gucunski, N., Kim, J., & Duong, T. H. (2016). Understanding depth-amplitude effects in assessment of GPR data from concrete bridge decks. NDT and E International, 83, 48–58.

**24.** Tesic, K., Baricevic, A., Serdar, M., & Gucunski, N. (2022). Characterization of ground penetrating radar signal during simulated corrosion of concrete reinforcement. Automation in Construction, 143, 104548.

**25.** Hong, S., Chen, D., & Dong, B. (2022). Numerical simulation and mechanism analysis of GPR-based reinforcement corrosion detection. Construction and Building Materials, 317, 125913.

**26.** Rhee, J. Y., Shim, J., Kee, S. H., & Lee, S. Y. (2020). Different characteristics of radar signal attenuation depending on concrete condition of bare bridge deck. KSCE Journal of Civil Engineering, 24(7), 2049–2062.

**27.** Lachowicz, J., & Rucka, M. (2019). A novel heterogeneous model of concrete for numerical modelling of ground penetrating radar. Construction and Building Materials, 227, 116703.

**28.** Asadi, P., Gindy, M., & Alvarez, M. (2019). A machine learning based approach for automatic rebar detection and quantification of deterioration in concrete bridge deck ground penetrating radar B-scan images. KSCE Journal of Civil Engineering, 23(6), 2618–2627.

**29.** Kaur, P., Dana, K. J., Romero, F. A., & Gucunski, N. (2016). Automated GPR rebar analysis for robotic bridge deck evaluation. IEEE Transactions on Cybernetics, 46(10), 2265–2276.

**30.** Ahmed, H., Le, C. P., & La, H. M. (2023). Pixel-level classification for bridge deck rebar detection and localization using multi-stage deep encoder-decoder network. Developments in the Built Environment, 14, 100132.

**31.** Xiong, X., & Tan, Y. (2023). Deep learning-based detection of tie bars in concrete pavement using ground penetrating radar. International Journal of Pavement Engineering, 24(2), 2155648.

**32.** Chang, C. W., Lin, C. H., & Lien, H. S. (2009). Measurement radius of reinforcing steel bar in concrete using digital image GPR. Construction and Building Materials, 23(2), 1057–1063.

**33.** Giannakis, I., Giannopoulos, A., & Warren, C. (2021). A machine learning scheme for estimating the diameter of reinforcing bars using ground penetrating radar. IEEE Geoscience and Remote Sensing Letters, 18(3), 461–465.

**34.** Zhang, Y., Gao, Z., Wang, X., & Liu, Q. (2023). Image representations of numerical simulations for training neural networks. Computer Modeling in Engineering & Sciences, 134(2), 821–833.

**35.** Xiang, Z., Ou, G., & Rashidi, A. (2020). An innovative approach to determine rebar depth and size by comparing GPR data with a theoretical database. In Construction Research Congress 2020. Reston, VA: American Society of Civil Engineers, 86–95.

**36.** Zhuang, X., Guo, H., Alajlan, N., Zhu, H., & Rabczuk, T. (2021). Deep autoencoder based energy method for the bending, vibration, and buckling analysis of Kirchhoff plates with transfer learning. European Journal of Mechanics. A, Solids, 87, 104225.

**37.** Liu, F., Liu, J., & Wang, L. (2022). Deep learning and infrared thermography for asphalt pavement crack severity classification. Automation in Construction, 140, 104383.

**38.** Park, S., Kim, J., Jeon, K., Kim, J., & Park, S. (2021). Improvement of gpr-based rebar diameter estimation using yolo-v3. Remote Sensing, 13(10), 2011.

**39.** Kuchipudi, S. T., Ghosh, D., & Gupta, H. (2022). Automated assessment of reinforced concrete elements using ground penetrating radar. Automation in Construction, 140, 104378.

**40.** Xue, C., Xia, Y., Wu, M., Chen, Z., Cheng, F., & Yun, L. (2024). EL-YOLO: An efficient and lightweight low-altitude aerial objects detector for onboard applications. Expert Systems with Applications, 256, 124848.

**41.** Lin, H., Parsi, A., Mullins, D., Horgan, J., Ward, E., Eising, C., et al. (2024). A study on data selection for object detection in various lighting conditions for autonomous vehicles. Journal of Imaging, 10(7), 153.

**42.** Li, L., Yang, L., Hao, Z., Sun, X., & Chen, G. (2024). Road sub-surface defect detection based on gprMax forward simulation-sample generation and Swin Transformer-YOLOX. Frontiers of Structural and Civil Engineering, 18(3), 334–349.

**43.** Alzubi, J., Nayyar, A., & Kumar, A. (2018). Machine learning from theory to algorithms: An overview. Journal of Physics: Conference Series, 1142, 012012.

**44.** Liao, L., Li, H., Shang, W., & Ma, L. (2022). An empirical study of the impact of hyperparameter tuning and model optimization on the performance properties of deep neural networks. ACM Transactions on Software Engineering and Methodology, 31(3), 1–40.

**45.** Li, J., Cheng, K., Wang, S., Morstatter, F., Trevino, R. P., Tang, J., & Liu, H. (2017). Feature selection: A data perspective. ACM Computing Surveys, 50(6), 1–45.

**46.** Mumuni, A., & Mumuni, F. (2022). Data augmentation: A comprehensive survey of modern approaches. Array, 16, 100258.

**47.** Raschka, S. (2018). Model evaluation, model selection, and algorithm selection in machine learning. arXiv preprint arXiv:1811.12808.

**48.** Singh, V., Pencina, M., Einstein, A. J., Liang, J. X., Berman, D. S., & Slomka, P. (2021). Impact of train/test sample regimen on performance estimate stability of machine learning in cardiovascular imaging. Scientific Reports, 11(1), 14490.

**49.** Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., et al. (2021). A comprehensive survey on transfer learning. Proceedings of the IEEE, 109(1), 43–76.

**50.** Manataki, M., & Vafidis, A. (2021). GPR data interpretation approaches in archaeological prospection. Applied Sciences, 11(16), 7531.

**51.** Yang, C. C. (2006). Image enhancement by modified contrast-stretching manipulation. Optics and Laser Technology, 38(3), 196–201.

**52.** Lashgari, E., Liang, D., & Maoz, U. (2020). Data augmentation for deep-learning-based electroencephalography. Journal of Neuroscience Methods, 346, 108885.

**53.** Bianchini Ciampoli, L., Tosti, F., Economou, N., & Benedetto, F. (2019). Signal processing of GPR data for road surveys. Geosciences, 9(2), 96.

**54.** Benedetto, A., Tosti, F., Bianchini Ciampoli, L., & D'Amico, F. (2017). An overview of ground-penetrating radar signal processing techniques for road inspections. Signal Processing, 132, 201–209.

**55.** Girshick, R., Donahue, J., Darrell, T., & Malik, J. (2014). Rich feature hierarchies for accurate object detection and semantic segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. Columbus, OH: IEEE, 580–587.

**56.** Girshick, R. (2015). Fast R-CNN. In Proceedings of the IEEE International Conference on Computer Vision. Santiago: IEEE, 1440–1448.

**57.** Wu, Y., Kirillov, A., Massa, F., Lo, W.-Y., & Girshick, R. (2019). Detectron2.

**58.** Kumar, P. K., & Kumar, N. K. (2023). Drone-based apple detection: Finding the depth of apples using YOLOv7 architecture with multi-head attention mechanism. Smart Agricultural Technology, 5, 100311.

**59.** Padilla, R., Netto, S. L., & da Silva, E. A. (2020). A survey on performance metrics for object-detection algorithms. In 2020 International Conference on Systems, Signals and Image Processing. Niteroi: IEEE, 237–242.

**60.** Terven, J., & Cordova-Esparza, D. (2023). A comprehensive review of YOLO: From YOLOv1 to YOLOv8 and beyond. arXiv preprint arXiv:2304.00501.

**61.** Google Colab. (2025). Google Colaboratory.

**62.** Gholamy, A., Kreinovich, V., & Kosheleva, O. (2018). Why 70/30 or 80/20 relation between training and testing sets: A pedagogical explanation. International Journal of Intelligent Technology and Applications, 11(2), 105–111.

**63.** Harris, C. R., Millman, K. J., Van Der Walt, S. J., Gommers, R., Virtanen, P., Cournapeau, D., et al. (2020). Array programming with NumPy. Nature, 585(7825), 357–362.

**64.** Hunter, J. D. (2007). Matplotlib: A 2D graphics environment. Computing in Science and Engineering, 9(3), 90–95.

**65.** Juan, Y., Ke, Z., Chen, Z., Zhong, D., Chen, W., & Yin, L. (2024). Rapid density estimation of tiny pests from sticky traps using Qpest RCNN in conjunction with UWB-UAV-based IoT framework. Neural Computing and Applications, 36(17), 9779–9803.

**66.** Liu, C., Yao, Y., Li, J., Qian, J., & Liu, L. (2024). Research on lightweight GPR road surface disease image recognition and data expansion algorithm based on YOLO and GAN. Case Studies in Construction Materials, 20, e02779.