Training AlexNet to classify Ground Penetrating Radar images featuring buried structures

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Keywords: *Ground Penetrating Radar (GPR), AlexNet, CNNs, classification, archaeological prospection*

Abstract

Ground Penetrating Radar (GPR) data derived from archaeological surveys are well known for their compexity, and their subsequent interpretation is time consuming requiring experience, expert skills, and a deeper understanding of GPR attributes. Hence a system capable of identifying patterns related to an archaeological context could significantly improve the interpretation process. Convolutional Neural Networks (CNNs) seem to be a promising approach towards an automated GPR data analysis, considering the exciting developments and improvements they brought in several computer vision tasks like image classification, segmentation, and object detection. In this study, the AlexNet CNN architecture was implemented in Python using Tensorflow and Keras libraries and trained to classify GPR C-scans collected from several archaeological sites. The training datasets were made from scratch, while the classification labels were set after patterns identified as buried structures, stripping noise, and other features of geological or anthropogenic origin. These three feature classes usually co-exist in GPR images and often exhibit similar patterns, making interpretation challenging thus increasing uncertainty. The Stochastic Gradient Descent with momentum was used in the training process, while Batch Normalization and Dropout techniques were also employed to improve the resulting classification. The learning curves of the loss function and classification accuracy were used for the training performance evaluation.