

# On the use of Convolutional Neural Networks to Classify Objects in GPR Scans

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**Abstract**—This paper presents the experimental validation of a CNN architecture for the classification of buried objects scanned using Ground Penetrating Radar (GPR) scans. Moreover, it introduces a dataset called DERCGPR consisting of 200 GPR scans of 7 buried objects.

Keywords-GPR; CNN; Neural Network; Classification

## I. INTRODUCTION

Ground Penetrating Radar (GPR) scans are commonly used to inspect shallow underground objects as a cost-effective, and non-destructive method of prospection [1]. Current applications of this technology require trained specialists to interpret GPR scans and identify buried objects. This leads to a time-consuming and costly process [2]. Section II of this paper summaries the process of data collection and post processing, while Section III shows the preliminary results.

## II. METHOD

### A. GPR Data Collection and Postprocessing

To collect the data, the GPR was installed on a 2-axis positioning system. Seven different objects buried underneath dry sand at depths between 5cm and 15cm were scanned. The hardware consisted of a NanoVNA connected to two Vivaldi antennas placed at 30cm above the surface. The VNA was set to emit a signal with frequency content between 700MHz and 3GHz every 1cm.

For every run, the A-scans were stacked to form the 2-dimensional B-scans on which the inverse fast Fourier transformation was applied row-wise (constant depth) using the PyTorch library. The real and imaginary parts of the result were summed and normalized across the whole dataset to preserve the small differences in signals reflecting from different materials. Finally, the row-wise mean was subtracted from every B-scan and negative values are eliminated by taking the absolute values.

### B. Neural Network Architecture

The designed neural network begins with two convolutional layers, each one followed by one ReLU activation layer, see Figure 1 for reference. Only one average pooling step was added after the first convolutional layer. Following those feature extraction layers, two linear layers with sizes 400, and 100, respectively, were added as the classifier. For verification, the architecture was trained to classify GPR scans of 7 different classes of buried

objects, leveraging every detail available in the acquired scans. A proprietary dataset of 1,390 training and 610 evaluation scans was used to train and test the devised model.

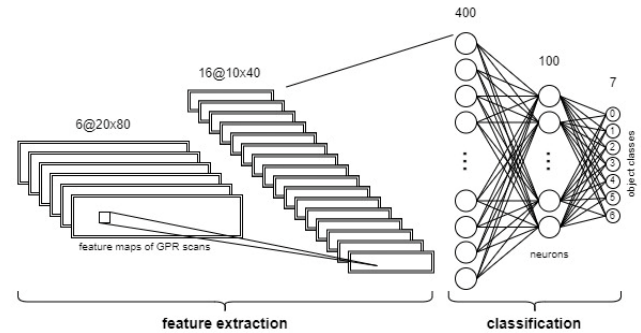


Figure 1: a diagram of the devised architecture for the classification task, showing the different types and sizes of layers.

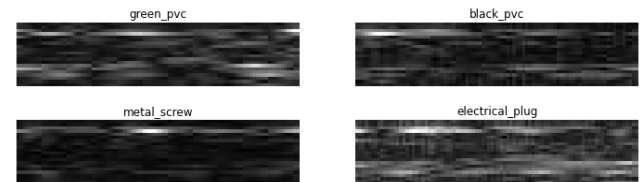


Figure 2: B-scans of different objects after applying inverse discrete Fourier transform, normalization and standardization.

## III. CONCLUSION

The resulting GPR scans, shown in Fig. 2, are rich in information representing the different buried materials. It is unclear to the untrained eye what objects those scans represent. Meanwhile, a neural network can extract intricate features that are used to identify and classify the buried objects. The obtained performance in classifying GPR scans is quiet promising. Training a neural network to perform this classification task is potentially both a time and a cost saving approach. In the future, the built model would greatly benefit from more training examples and increased detail in the collected GPR measurements.

## REFERENCES

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