MATERIAL CLASSIFICATION OF UNDERGROUND OBJECTS FROM GPR RECORDINGS USING DEEP LEARNING APPROACH

Daniel Štifanić[1], Jelena Štifanić[1], Sandi Baressi Šegota[1], Nikola Anđelić[1], Zlatan Car[1]

[1] University of Rijeka – Faculty of Engineering, Vukovarska 58, 51000 Rijeka, Croatia
e-mail: dstifanic@riteh.hr, jmusulin@riteh.hr, sbaressisegota@riteh.hr, nandelic@riteh.hr, car@riteh.hr

Abstract:

Exploration and detection of underground objects without excavation can be achieved by utilizing ground penetrating radar. Since such an approach is nondestructive, electromagnetic radiation has been used in order to accomplish sub-surface surveying. The correct interpretation of acquired ground penetrating radar data can be demanding, time-consuming and very challenging especially when the observed environment is noisy. However, with the assistance of artificial intelligence algorithms, such data can be processed and analyzed at high speed and with high accuracy. The aim of this research was to develop a deep learning model for the material classification of underground objects from ground penetrating radar recordings. Within the recordings, the pipes are usually visually represented as hyperbola-shaped features of different characteristics. Annotated by experts and preprocessed ground penetrating radar recordings were used as input to the deep convolutional neural networks. After the model was fully trained, performance on the validation set showed that the developed model can be used for pipe material classification from ground penetrating radar recordings with satisfactory results.

Keywords: ground penetrating radar, artificial intelligence, deep learning, convolutional neural network, classification

1. Introduction

Nowadays, it is essential for communal services such as water supply and energy sector to be equipped with modern technological solutions. By integrating such solutions into existing systems avoidable losses can be minimized, thereby the overall efficiency can be increased [1]. Unfortunately, data that represent underground infrastructure that is stored one or more decades ago are usually incomplete and low-quality. However, by utilizing advanced devices, underground utilities can be observed and explored from the ground surface without the need for excavation [2]. Such sub-surface surveying can be accomplished with electromagnetic radiation produced by ground penetrating radar (GPR). Using the aforementioned approach, the process of underground exploration is simplified but the proper identification of underground utilities can be very demanding and challenging which usually requires the support of a trained expert [3]. Data obtained by GPR can be processed in order to visually represent the observed underground as an image. The width of the image corresponds to the distance traveled by the radar itself, and the height directly corresponds to the depth of electromagnetic wave penetration into the ground [2].

Images acquired in the aforementioned way can be used to train deep learning models based on convolutional neural networks [4].

In this research, underground utilities of interest are pipes, more precisely different materials of pipes such as metal and plastic. Within the GRP recordings, the pipes are usually visually represented as hyperbola-shaped features of different characteristics. Additionally, different pipe material will result in a feature with different characteristics within the GPR recording.

The aim of this research is to determine the performances of deep learning models for the material classification of underground objects from GPR recordings. Additionally, a fully trained model can significantly reduce the time required for manual processing and analysis of such image data.

2. Materials and Methods

The data used in this research consists of 2216 GPR recordings which are manually annotated by the experts resulting in a total of 3794 patches representing the pipe feature. Patches can be divided into two classes, more precisely metal pipe class, and plastic pipe class. For validation purposes, 759 patches are randomly selected leaving the 3035 patches for model training purposes. Moreover, the obtained dataset of patches is unbalanced with 2590 metal features and 1204 plastic features.

Deep convolutional neural networks (CNNs) basically revolutionized computer vision since they are designed to learn spatial hierarchies of features automatically and adaptively from given data [5]. Over the years, CNN-based models achieved cutting-edge results in many tasks including image classification, object detection, and semantic segmentation. In this research, ResNet50 and Xception architectures are used to perform binary classification of pipe material from the GPR recordings.

In 2015, the ResNet architecture was presented by He et al. when it won the ILSVRC 2015 competition with an error of 3.6% on the ImageNet test set [6]. This research utilizes ResNet50 architecture in which, every 2-layer block is replaced (in the 34-layer network) with a 3-layer bottleneck block resulting in a total of 50 layers. The number of trainable parameters in such architecture is 23 888 771. Furthermore, in 2017, Chollet proposes a novel deep CNN architecture named Xception which is inspired by Inception. In such architecture, the Inception modules have been replaced with depthwise separable convolutions with the aim of performance improvement [7]. The proposed architecture consists of 36 convolutional layers which are structured into 14 modules, all of which have so-called linear residual connections around them (not including the first and last module). In other words, the architecture can be described as a linear stack of depthwise separable convolution layers with residual connections.

In order to evaluate the performances of the aforementioned deep CNN architectures, accuracy and area under the ROC curve (AUC) metrics are used [8]. Additionally, a confusion matrix is utilized in order to visually interpret the obtained results.

3. Results and Discussion

The experimental results are achieved with ResNet50 and Xception architectures. Additionally, in both cases at the top of the base architecture after the global average pooling layer, the dropout layer with the value of 0.2 and the output layer with two neurons and softmax activation function were added. Base layers of both architectures are pretrained on ImageNet while the added layers are initialized randomly. In the first stage, the newly added layers are trained using the Adam optimization algorithm with a learning rate of 0.001, while the base layers were frozen. In order to prevent overfitting, early stopping was used. In the second stage, the newly added layers were frozen while base layers were trained with a lower value of learning rate (0.0001) to ensure more stable training and convergence. The aforementioned training approach was used for the ResNet50 and Xception architecture. The results of performance evaluation on the validation set in terms of accuracy and AUC are shown in Figure 1.

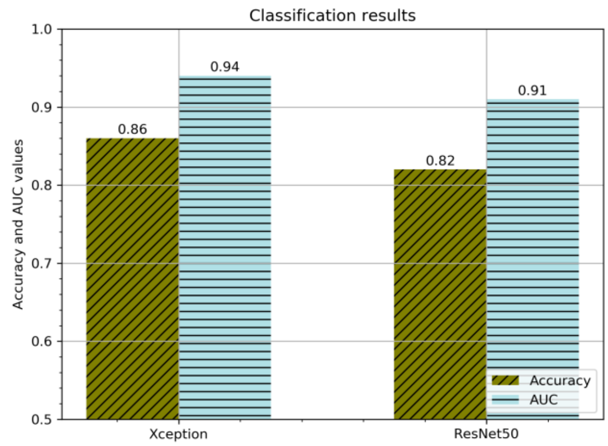

Fig. 1. Performances of ResNet50 and Xception architectures in terms of accuracy and AUC

From Fig. 1. it is evident that the Xception architecture in the previously described configuration achieves better results with an accuracy value of 0.86 and an AUC value of 0.94. The ResNet50 architecture resulted in performance values of 0.82 (accuracy) and 0.91 (AUC). In order to get a more detailed interpretation of the obtained results, confusion matrices were created. The confusion matrix in the case of the ResNet50 architecture is shown in Fig. 2. (left), while one in the case of the Xception architecture is shown in Fig. 2. (right).

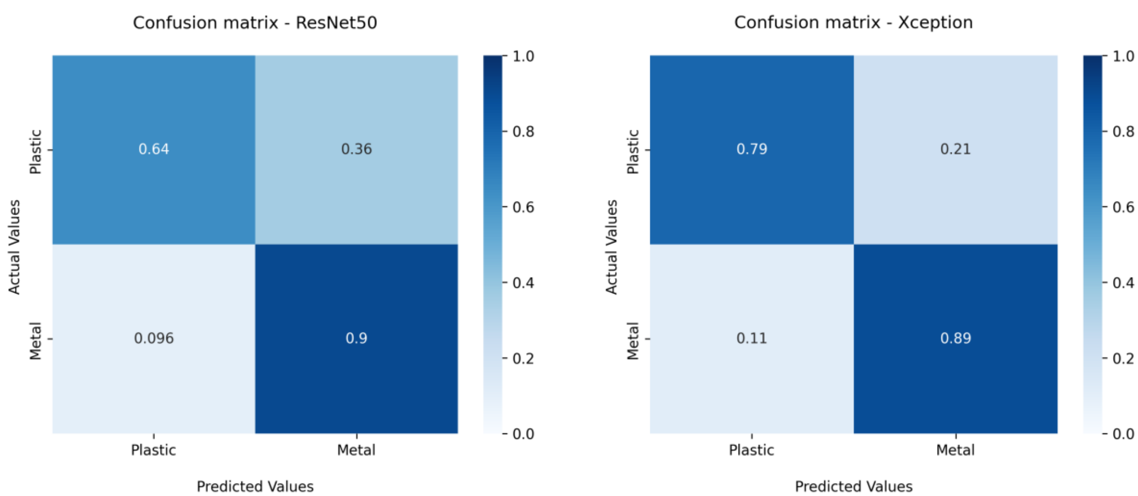

Fig. 2. Confusion matrix of ResNet50 (left) and Xception (right) architectures

Using the Xception architecture, the model successfully classified 89% of metal, and 79% of plastic pipes. 11% of metal pipes were classified as plastic and 21% of plastic pipes were classified as metal. In the case of the ResNet50 architecture, the metal pipe was correctly classified in 90% of the cases, while in 9.6% of the cases the label “plastic” was assigned. Plastic pipes were correctly classified in 64% of cases but in 36% of cases, the “metal” label was assigned to plastic pipes.

The presented results show that the Xception architecture provides satisfactory results considering that the classification of pipe materials based on radar reflection is a very challenging task and many factors affect the outcome. Implementation of a fully trained classification model will be used in future work together with an object detection algorithm in order to provide additional information about the type of material the pipe is made of.

4. Conclusions

According to the obtained performances of classification models, it can be concluded that deep CNNs have great potential in pipe material classification from GPR recordings. Xception architecture adapted to the problem of this research along with the training process with frozen layers resulted in satisfactory results with values of 0.86 (accuracy) and 0.94 (AUC). The unbalanced number of patches per class was a limitation of this research, therefore future work should use a more balanced dataset. The presented approach will be used in future work along with the object detection model in order to fully automate the process of detection, localization and classification of underground infrastructure.

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