A Deep Learning Approach for Tree Root Detection using GPR Spectrogram Imagery

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Abstract*— Monitoring and conservation of natural resources such as trees have become necessary as the impact of new diseases attacking the integrity of trees has created major concerns for environmentalists and communities in recent years. Within this context, tree roots are one of the plants' most important and vulnerable organs as well as one of the most challenging ones to inspect. Tree roots naturally are developed under the ground, hence difficult to be seen and access. To that effect, the non-destructive testing (NDT) methods have become one of the preferred methods of tree roots assessment and monitoring as opposed to other conventional and destructive techniques. The applications of the ground penetrating radar (GPR) have proven to be an accurate approach and methodology for the investigation and mapping of tree roots. However, a major challenge for GPR detection of tree roots architecture and pattern accurately is the soil inhomogeneity, including the presence of various natural and artificial features within the soil. This study aims to mitigate the uncertainty in root detection by proposing a deep learning method based on the analysis of GPR spectrograms (i.e., a graphic representation of a signal's frequency spectrum with respect to time). In this study, the GPR signal is first processed in both the time and frequency domains to filter the existing noise-related information and hence, to produce spectrograms. Subsequently, an image-based deep learning framework is implemented, and the effectiveness in detecting tree roots is analysed in comparison with conventional feature-based machine learning classifiers. The preliminary results of this research demonstrate the potential of the proposed approach and pave the way for the implementation of new methodologies in assessing tree root systems.

***Keywords*—Ground penetrating radar (GPR), tree roots assessment, deep learning, spectrograms**

I. INTRODUCTION

Humanity and wildlife greatly depend on trees and forest ecosystems. Oxygen production, carbon storage, soil stability, food production, and wildlife habitats are only a few examples of the significant advantages of the world's natural heritage. Also, the impact of trees on human health and behaviour is scientifically documented as, amongst others, they contribute to reducing noise and pollution and fostering social interaction [1].

Roots, more than any other tree organ, are critical to the health of plants and trees. They serve as the anchorage and support for the tree, absorbing soil minerals and water, storing nutrients, and synthesising hormones [2]. Tree roots' spatial development follows stochastic patterns that can vary significantly between tree species. Additionally, as tree patterns frequently correlate with a tree's health condition, their assessment has been extensively utilised as a diagnostic tool in arboriculture applications [3].

Numerous strategies have been developed to efficiently map the root structure of a tree, which can be classified as destructive or non-destructive testing (NDT) methods. Excavation, uprooting, and profile wall techniques all fall under the destructive methods category [4]. Apart from being inefficient and unsuitable for large-scale forestry applications, these techniques are not recommended by stakeholders because they can also inflict permanent damage to the environment [5]. By contrast, NDT approaches may efficiently map root patterns without interfering with the host material or causing irreversible damage to the tree. Numerous NDT methods have been used for root mapping, including X-ray tomography, nuclear approaches, magnetic resonance, electrical resistivity tomography and acoustic techniques [4]. Ground penetrating radar (GPR) is an NDT method with a wide range of applications, including civil and environmental engineering, landmine detection, and archaeology. GPR has proven to be a very appealing alternative to conventional inspection methods in forestry applications due to its ease of use, adaptability, and high resolution. Hence, GPR is gaining popularity as a non-destructive tool for estimating root patterns. Recent research has focused on methods for automatic root mapping in three-dimensional settings [6]. Additionally, recent studies have proposed a new signal processing approach and demonstrated the feasibility of a combined time-frequency analysis of the GPR signal [7].

Nevertheless, one of the main difficulties in investigating tree roots with GPR lies in the heterogeneity of the soils in which these are embedded. The coexistence of soils with different dielectric properties, together with the occurrence of

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other buried objects such as stones, contribute to making the GPR signal analysis difficult. It is therefore necessary to identify techniques that are effective in recognising the roots' response in the GPR signal, minimising the occurrence of false positives due to the presence of other targets. Within this context, machine learning (ML) and deep learning (DL) classifiers stand as a very effective choice when it is impractical to implement traditional algorithms.

II. Aim & Objectives

This research aims to demonstrate the ability of DL image-based detection and classification methods to effectively recognise tree roots embedded in natural heterogeneous soils, thus eliminating the uncertainty due to the presence of other buried objects.

The objectives of this research are to (*i*) convert the GPR signal into spectrograms (i.e., a 2D graphic representation of a signal's frequency spectrum changing over time); (*ii*) use these 2D GPR spectrograms as the input of conventional feature-based ML classifiers; (*iii*) to test the same spectrograms using innovative image-based DL methods, so as to evaluate whether the detection of tree roots could be further enhanced as compared to conventional ML approaches.

III. Methodology

A. GPR Test Site and Equipment

The GPR survey was carried out in Gunnersbury Park, Ealing, London (United Kingdom), as part of a major investigation [6]. A set of 36 semi-circular scans were performed around the investigated tree. The first survey transect was positioned 0.50 m from the bark, whereas the spacing between the lines of scan was set to 0.30 m. Consequently, an overall area of 218.04 m^2 was surveyed around the tree, with an outer radius of 11.86 m and an inner radius of 1.36 m (Fig.1).

The survey was performed using the Opera Duo ground-coupled GPR system, manufactured by IDS GeoRadar (Part of Hexagon) and equipped with 700 MHz and 250 MHz central frequency antennas. Data were collected using a time window of 80 ns, discretised across 512 samples. The horizontal resolution was set to 3.06×10^{-2} m. To effectively investigate the whole tree root system's architecture without impacting the signal resolution, data collected with the 250 MHz antenna were discarded for the analysis carried out in this paper.

Subsequently, an excavation was carried out within the surveyed area for validation purposes. An area of 16 m^2 was identified based on the coordinates of the GPR investigation, and soil was accurately excavated in layers of c.a. 0.10 m at a time to expose the root system.

B. Data Processing Methodology

1) GPR Signal Processing

This stage is aimed at reducing noise-related features in the GPR data, so as to produce measurable information and readily interpretable imagery for further results analysis. Data are

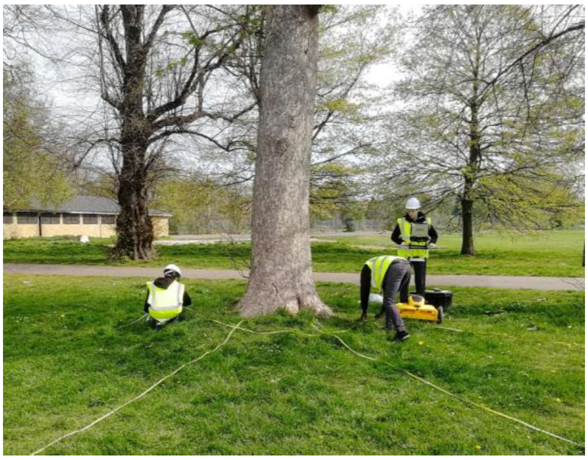

Fig. 1. The investigated area

therefore processed using a multi-stage methodology, using filters operating both in time and in frequency domains:

- Zero-offset removal
- Time-zero correction
- Time-varying gain
- Singular value decomposition (SVD) filter
- Band-pass filtering

Subsequently, spectrograms of the GPR signal (Fig. 2) are created by applying the Short-Time Fourier Transform (STFT) as follows:

$$STFT(t,\omega) = \int_{\tau} [x(t) \cdot w(\tau - t)] \cdot e^{-j\omega t} dt \tag{1}$$

where STFT is the frequency energy at time t and frequency ω, x is the reflected amplitude and w is the window function.

2) Data Categorisation

To train the ML algorithms, it is necessary to divide the image dataset into categories, so that the ML classifiers can identify

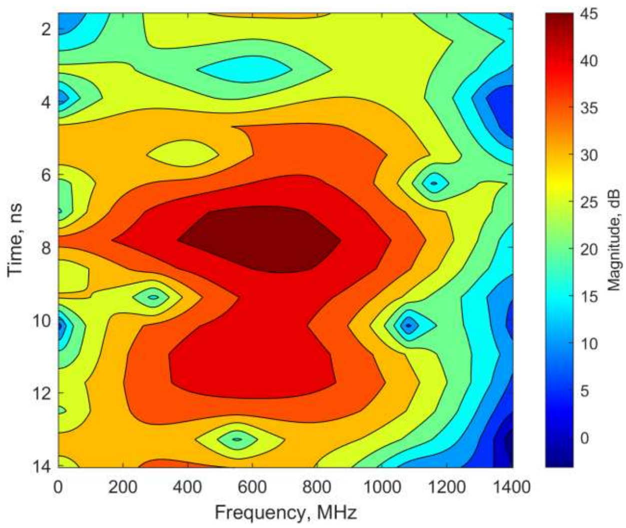

Fig. 2. Spectrogram of the GPR signal over a tree root

features from different targets and discriminate between them correctly. In this study, four categories are used to represent the characteristics observed from the field excavation activities, as follows:

- Roots
- Root clusters
- Stones
- No target

Furthermore, to increase the dataset size and the performance of the investigated detection methods, the spectrograms are corrupted with Gaussian noise, with a noise variance varying from 0.1 to 1.

3) Feature Extraction

Feature extraction is an essential requirement for building up a ML classifier. For the purposes of the present study, eight features are extracted from the spectrogram images, i.e., standard deviation, median, mode, mean (grey) value, integrated density, centre of mass, and skewness and kurtosis.

4) Conventional ML Detection Methods

To discriminate between the presence or absence of roots or other buried targets in heterogeneous soils, the previously extracted features are initially used as inputs in different conventional ML models [8]:

- Support Vector Machine (SVM): supervised learning model that maps the training dataset in space, so as to maximise the width of the gap between the investigated categories. The testing dataset is then mapped into the same space and predicted to belong to a category based on its position;
- Decision Tree (DT): supervised learning model where the data are progressively split according to set parameters. While the nodes specify a test on an attribute, the branches descending from that node correspond to one of the possible values for that attribute;
- Naive Bayes (NB): simple probabilistic classifier based on the application of the Bayes' theorem with strong independence assumptions between the model features;
- Artificial Neural Networks (ANN): computing systems inspired by the biological neural networks forming human brains. A generic NN with three levels is used, namely two dense layers and an output layer, each composed of 32 neurons.

5) Image-Based DL Detection Methods

To evaluate if the tree roots' detection could be further improved, the spectrograms are tested using the following image-based DL algorithms:

- SqueezeNet [9]: a smaller NN that is 18 layers deep. It has fewer parameters, and therefore requires less computational effort, memory requirements and running time.
- VGG-16 [10]: a convolutional neural network (CNN) that is 16 layers deep. It is an extensive network, as it counts around 138 million parameters, which take significant time to train. Nevertheless, the simple and uniform architecture of VGG-16 makes this CNN an appealing choice.

IV. Main Results and Short Discussion

The proposed DL classifiers are compared with the conventional ML classifiers described in the previous Section to evaluate their performance in tree roots detection. Fig. 3 shows the overall accuracy of each analysed detection method as the noise intensity varies (noise variance equals to 0.1, 0.5 and 1, respectively).

It can be noted that the performance of all the classifiers decreases as the noise's incidence increases, as expected. However, in all the investigated cases, the ANN and the proposed VGG-16 show significantly higher accuracy than the conventional classifiers. In more detail, the accuracy for the ANN variates between 100% - 99%, whereas the VGG-16 ranges between 100% - 96%. The SqueezeNet classifier also shows solid results for a noise variance between 0.1 and 0.5, with an accuracy ranging between 100% - 98%. However, as the noise variance increases to 1, the SqueezeNet accuracy drops significantly to 65%. As for the conventional classifiers, the DT is the only one showing stable results for all the noise intensities, with an accuracy ranging between 88% - 78%. The SVM and NB methods are the least accurate for such investigation, as their accuracies drop significantly from 90% to 32% and from 73% to 23%, respectively. It is therefore evident how the proposed DL detection framework is more robust and effective than traditional ML methods.

The accuracy of the results is further investigated by means of the following performance metrics:

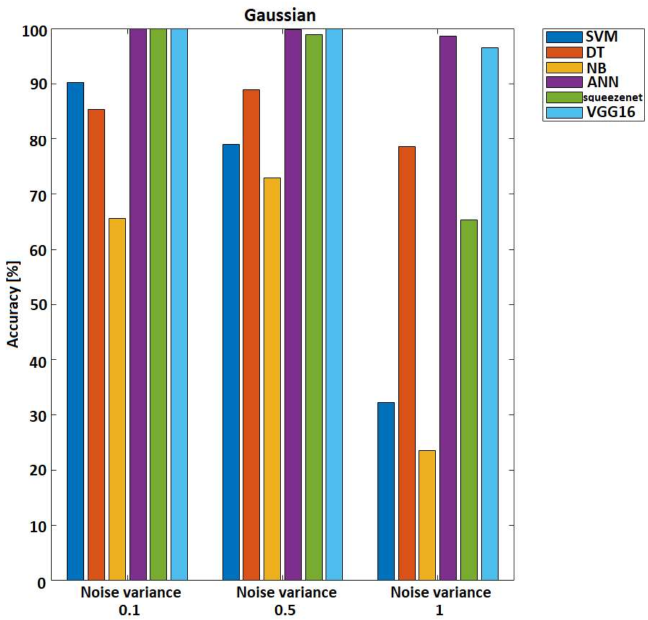

Fig. 3. Overall accuracy of the conventional and image-based DL classifiers, for increasing values of Gaussian noise.

TABLE I. PERFORMANCE METRICS FOR THE CONVENTIONAL AND PROPOSED IMAGE-BASED DL CLASSIFIERS (NOISE VARIANCE 0.1)

	SVM	DT	NB	ANN	SqueezeNet	VGG-16
Precision	0.914	0.890	0.681	0.999	1	1
Recall	0.903	0.854	0.656	0.999	1	1
F-measure	0.899	0.824	0.647	0.999	1	1

TABLE II. PERFORMANCE METRICS FOR THE CONVENTIONAL AND PROPOSED IMAGE-BASED DL CLASSIFIERS (NOISE VARIANCE 0.5)

	SVM	DT	NB	ANN	SqueezeNet	VGG-16
Precision	0.818	0.893	0.740	0.999	0.987	1
Recall	0.793	0.889	0.732	0.999	0.990	1
F-measure	0.783	0.886	0.718	0.999	0.987	1

TABLE III. PERFORMANCE METRICS FOR THE CONVENTIONAL AND PROPOSED IMAGE-BASED DL CLASSIFIERS (NOISE VARIANCE 1)

	SVM	DT	NB	ANN	SqueezeNet	VGG-16
Precision		0.812	0.444	0.994	0.617	0.962
Recall	0.323	0.786	0.235	0.994	0.695	0.962
F-measure		0.777	0.110	0.994	0.600	0.962

- Precision: the ratio between relevant cases and the retrieved cases;
- Recall: the ratio between relevant cases and all the cases in the dataset;
- F-measure: a measure of a test's accuracy. It is calculated as the harmonic mean of precision and recall.

The values of precision, recall and F-measure for the conventional and DL classifiers are reported in Tables I, II and III, for noise intensities of 0.1, 0.5 and 1, respectively. Results confirm that the proposed VGG-16 has very high levels of accuracy for all the investigated cases, comparable to the results obtained with the ANN and outperforming the results, albeit robust, obtained with the DT. The SqueezeNet classifier also confirms very accurate results for low to medium levels of noise, but performance levels decrease sensibly for high noise intensities.

V. CONCLUSION

The present study reports the preliminary findings of a novel research within the framework of ground penetrating radar (GPR) applications for root systems' detection and assessment. The main focus of this study is to investigate the viability of a processing methodology based on deep learning (DL) image-based detection methods for root detection in heterogeneous soils, so as to effectively reduce the uncertainty given by the presence of other buried objects. To this extent, a GPR dataset was collected over a tree root system, which was subsequently partially exposed through excavation for validation purposes. GPR data were converted into spectrogram using the Short-Time Fourier Transform (STFT) technique and analysed with both conventional machine learning (ML) classifiers and two proposed DL classifiers, namely SqueezeNet and VGG-16. The comparison of results has shown that the proposed DL framework is capable of discerning tree roots from other buried objects with great accuracy. In particular, the VGG-16 outperforms all the other classifiers, despite the images having been corrupted with Gaussian noise of increasing intensity to better evaluate the models' performance. The achieved results pave the way to further developments for a more reliable and advanced GPR-based assessment of tree root systems.

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