A Machine Learning Based Fast Forward Solver for Ground Penetrating Radar

INTERNSHIP REPORT

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It is with great enthusiasm and spirit I am bringing out this project report. I also feel that it is the right opportunity to acknowledge the support and guidance that came in from various quarters during the course of the completion of my project.

I wish to express my profound gratitude to my guide **Dr. Divya S Vidyadharan** for her amenable guidance which became the backbone for my project to make it a success. I am also thankful to all staff members in the **Augsenselab Private Limited**. Last but not least, I would like to thank all my friends and my parents who have given me constant encouragement throughout the course of this project.

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ABSTRACT

The forward modeling of Ground Penetrating Radar (GPR) data is essential for interpreting complex subsurface structures. However, conventional 3D full-wave electromagnetic (EM) solvers, such as those based on the Finite-Difference Time-Domain (FDTD) method, are computationally demanding, particularly for realistic GPR scenarios. In response to this challenge, we have developed a near real-time forward modeling framework for GPR using a machine learning (ML) architecture. The objective is to replace the widely used simulation tool gprMax with an ML-based model capable of generating A-scans specifically for applications involving concrete rebar detection.

Our approach involves the automated generation of diverse configuration files by varying key parameters such as rebar diameter, depth, and water content. These input files are processed by gprMax to produce corresponding A-scans, which are then downsampled and subjected to dimensionality reduction via Principal Component Analysis (PCA). The ML model is trained to predict the PCA components based on the input parameters, allowing for the subsequent reconstruction of the A-scan.

This method substantially reduces the computational burden associated with traditional simulation techniques while preserving accuracy. An additional advantage of the ML-based forward solver is its ability to rapidly generate A-scans across a wide range of scenarios, accounting for variations in rebar depth, diameter, and concrete water content—an otherwise challenging task for real-time simulations. This capability enables efficient analysis of GPR performance across diverse use cases within a short time frame. However, there is still room for improving the fidelity of A-scan reconstruction from the predicted PCA components.

Contents

Chapter 1

INTRODUCTION

Ground Penetrating Radar (GPR) is a widely utilized non-destructive electromagnetic tool for infrastructure assessment and geophysical investigations. The simulation, or forward modeling, of GPR data has become increasingly vital for interpreting complex real-world scenarios. Despite advancements in simulation accuracy and software capabilities, full-waveform three-dimensional (3D) electromagnetic (EM) forward solvers, particularly those employing the Finite-Difference Time-Domain (FDTD) method, remain computationally intensive. Attempts to simplify these models, such as 3D-to-2D transformations or the use of simplified antenna models, often fail to deliver accurate results, especially near or within the intermediate field of the GPR antenna.

To address these computational challenges, we propose a novel near real-time 3D forward modeling approach for GPR, leveraging machine learning (ML). Neural networks, a well-established ML technique, are known for their ability to identify complex patterns in multi-dimensional data spaces when trained with sufficient data. However, traditional deep neural networks face challenges, such as the requirement of large amount of training data, which have constrained their application in GPR modeling.

To overcome these limitations, we developed an advanced ML-based method capable of predicting complex interactions between the target, surface, and antenna while accounting for realistic dispersive losses. This approach involves parameterizing the GPR model and training the network using a combination of Principal

Component Analysis (PCA) and a comprehensive dataset generated from FDTD simulations. PCA effectively reduces the dimensionality of the data, enhancing the efficiency of the training process. Although generating the training dataset and training the neural network are computationally intensive tasks, they are one-time processes. Once trained, the network functions as a near real-time forward solver, delivering response times under one second. While our ML-based solver is tailored to specific scenarios, it is adaptable to a variety of GPR applications where the range of expected variations is constrained. This real-time forward solver has significant potential in non-destructive testing, particularly in civil engineering applications such as utility mapping, bridge evaluation, and crack detection. One of the most promising applications of our ML-based forward solver is the accurate estimation of rebar location, diameter, and moisture content within concrete structures.

Despite the widespread use of GPR, accurately assessing these parameters remains challenging. Traditional methods, such as hyperbola fitting for permittivity estimation and amplitude ratios for conductivity evaluation, often overlook critical factors like antenna directivity patterns and near-field effects, leading to inaccuracies. Our approach significantly reduces computational demands, making advanced GPR-based assessments more accessible and precise, even on computers with modest computational resources.

Chapter 2

LITERATURE SURVEY

1. Underground Cylindrical Objects Detection and Diameter Identification in GPR B-Scans via the CNN-LSTM Framework

Wentai Lei, Jiabin Luo, Feifei Hou, Long Xu, Ruiqing Wang and Xinyue Jiang.[1]

This paper [1] presents a novel automated scheme for the detection and diameter identification of underground cylindrical objects in GPR B-scans, leveraging a deep learning framework that integrates Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The proposed method addresses the challenges associated with traditional GPR data interpretation, which often relies on manual analysis and is susceptible to noise and inaccuracies.

The study introduces an Adaptive Target Region Detection (ATRD) algorithm designed to extract hyperbolic signatures from GPR B-scans, which are indicative of cylindrical objects. The CNN component of the framework is responsible for spatial feature extraction, while the LSTM component captures temporal dependencies within the data. This dual approach allows for a comprehensive analysis of the hyperbola regions, transforming the task of diameter identification into a classification problem. Experimental results demonstrate the effectiveness of the CNN-LSTM framework, achieving an accuracy of 99.5% on simulated datasets and 92.5% on field datasets. The framework outperforms traditional methods, including single CNN and LSTM networks, by significant margins, highlighting its robustness in identifying various diameters of underground cylindrical objects. The integration of spatial and temporal features enhances the model's ability to accurately interpret

GPR data, making it a promising tool for automated subsurface investigations.

This research contributes to the field of GPR data interpretation by providing a deep learning-based solution that minimizes manual intervention and improves accuracy in diameter identification. The findings underscore the potential of advanced machine learning techniques in enhancing the efficiency and reliability of GPR applications in civil engineering and related fields. Future work may explore the application of this framework to a broader range of underground objects and the incorporation of additional data modalities to further improve detection capabilities.

2.GPR Full-Waveform Inversion with Deep-Learning Forward Modeling

Ourania Patsia, Antonios Giannopoulos, Iraklis Giannakis.[2]

This paper presents a novel approach to Ground Penetrating Radar (GPR) data interpretation through the integration of deep-learning techniques with Full-Waveform Inversion (FWI). The authors propose a deep-learning-based forward solver that significantly enhances the efficiency and accuracy of GPR analysis, particularly for concrete structures. The methodology involves generating synthetic training data using the open-source FDTD solver gprMax, which simulates various concrete properties and embedded targets. The study demonstrates that the deep-learning model, when coupled with FWI, can effectively estimate the depth and radius of rebars within concrete, providing a practical tool for non-destructive testing. The results indicate that this approach not only accelerates the inversion process but also improves the reliability of the findings, making it commercially appealing for real-world applications.

The paper effectively addresses the challenges associated with traditional GPR data interpretation methods, which often rely on extensive experimental setups and can be computationally intensive. By utilizing synthetic data generated from gprMax, the authors circumvent the limitations of acquiring ground truth data in controlled environments, a common hurdle in supervised machine learning applications. The architecture of the deep-learning forward solver is well-detailed, highlighting the importance of training data in establishing accurate input-output relationships.The authors has represented a significant step forward in GPR data analysis, offering a promising framework that combines deep learning with traditional inversion techniques. The findings not only contribute to the academic discourse on GPR applications but also hold practical implications for industries reliant on concrete inspection and non-destructive testing methodologies. Future research could explore the applicability of this approach to other subsurface materials and conditions, further expanding the utility of deep-learning techniques in geophysical investigations.

3.A Machine Learning Based Fast Forward Solver for Ground Penetrating Radar with Application to Full Waveform Inversion

Iraklis Giannakis, Antonios Giannopoulos, and Craig Warren.[3]

The paper [3] by Giannakis et al. presents a novel approach to enhance the efficiency of Ground Penetrating Radar (GPR) systems through machine learning (ML) techniques. The authors address the computational challenges associated with traditional full-waveform inversion (FWI) methods, which often require significant resources and time, making them impractical for real-time applications.

The authors address the computational difficulties of traditional full-waveform inversion (FWI) methods, which require significant resources and time, making them unsuitable for real-time applications. They propose a machine learning (ML)-based forward solver that uses synthetic data from Finite Difference Time Domain (FDTD) simulations via the open-source software gprMax. This software simulates electromagnetic wave propagation to create a detailed training dataset that captures the interactions between the GPR antenna, target objects, and the surrounding medium. The training process employs principal component analysis (PCA) to reduce input data dimensionality, allowing for the training of a deep neural network with 120 layers, which can learn complex patterns in the data. The authors highlight the necessity of realistic dielectric properties of concrete and accurate GPR antenna modeling to validate the training data. The results indicate that the ML-based solver can predict GPR responses with high accuracy while significantly reducing computation time to about one second.

The architecture of the neural network is deep, comprising 120 layers, enabling it to learn intricate patterns and relationships within the data. The authors emphasize the importance of using realistic dielectric properties of concrete and accurately modeling the GPR antenna to ensure the validity of the training data. Results demonstrate that the ML-based solver can predict GPR responses with high accuracy, significantly reducing computation time to approximately one second, thus making it suitable for near real-time applications. In conclusion, Giannakis et al. provide a noteworthy contribution to the field of geoscience and remote sensing by introducing a fast and efficient ML-based forward solver for GPR, enhancing the capabilities of GPR systems and opening avenues for further research in integrating machine learning with geophysical methods, ultimately improving the accuracy and speed of subsurface investigations and highlighting the transformative potential of machine learning in addressing traditional computational challenges in geophysical applications.

4.Comprehensive GPR Signal Analysis via Descriptive Statistics and Machine Learning

Himan Namdari, Majid Moradikia, Douglas Todd Petkie , Radwin Askari†, Seyed Zekavat.[4]

The paper "Comprehensive GPR Signal Analysis via Descriptive Statistics and Machine Learning" by Himan Namdari et al. presents a thorough investigation into how various soil characteristics influence Ground Penetrating Radar (GPR) signals. Utilizing the gprMax simulation tool, the authors explore parameters such as dielectric properties, layer thickness, and surface roughness, demonstrating their significant impact on GPR signal behavior. The study employs descriptive statistical analysis to extract key features from the GPR data, including metrics like mean, standard deviation, skewness, and kurtosis, which enhance the interpretability of the signals. Furthermore, machine learning techniques, particularly the Random Forest model, are applied to assess feature importance, allowing for a more accurate characterization of subsurface conditions. The findings underscore the effectiveness of combining statistical and machine learning approaches to simplify complex GPR data, ultimately paving the way for improved soil moisture and subsurface analysis. This research contributes valuable insights into the application of GPR in various fields, including agriculture and civil engineering.

Chapter 3

PROBLEM STATEMENT AND OBJECTIVES

3.1 Problem Statement

To develop a machine learning-based fast forward solver that can replace the time-consuming and computationally intensive full-waveform solvers currently used in GPR simulations.

3.2 Objectives

- To design and implement a machine learning model capable of generating A-scans for concrete rebars with varying diameters, depths, and water content in the surrounding concrete.
- To create a comprehensive dataset of A-scans by systematically varying the diameter, depth, and water content, interpolating values within the expected range to ensure robust model training.

Chapter 4

METHODOLOGY

4.1 Dataset

The dataset utilized in this project comprises simulated A-scans generated to model the interaction of electromagnetic waves with subsurface materials, specifically focusing on concrete embedded with metallic rebars. These simulations were carried out using gprMax, a specialized software for simulating electromagnetic wave propagation in Ground Penetrating Radar (GPR) scenarios. The dataset captures a wide range of variables, including the diameter of rebars, their depth (cover thickness), and the moisture content of the surrounding concrete, ensuring comprehensive coverage of real-world conditions. Fig. 4.1 shows the extended debye properties of concrete in the work.

To ensure the robustness and generalizability of the machine learning model, the dataset was divided into training, validation, and test sets. Preprocessing steps, such as normalization and principal component analysis (PCA), were employed to reduce dimensionality and enhance the model's performance. The A-scan data, initially

WC	ϵ_s	ϵ_∞	t_0	σ ($\Omega^{-1}m^{-1}$)
12 %	12.84	7.42	0.611 ns	20.6×10^{-3}
9.3 %	11.19	7.2	0.73 ns	23×10^{-3}
6.2 %	9.14	5.93	0.8 ns	6.7×10^{-3}
5.5 %	8.63	6.023	1 ns	5.15×10^{-3}
2.8 %	6.75	5.503	2.28 ns	2.03×10^{-3}
0.2 %	4.814	4.507	0.82 ns	6.06×10^{-4}

Figure 4.1: Extended Debye Properties of Concrete

in the .in format, was converted to .out format for processing, with necessary data further analyzed using the proposed machine learning framework. Fig. 4.2 shows a sample input file generated for the simulation tool (.in file). Fig. 4.3 shows the corresponding output file generated by the simulation tool.

```
#title: GPR input file
#domain: 0.5 0.3 0.4
#dx_dy_dz: 0.001 0.001 0.001
#time_window: 3000
#material: 5.960844650290943 0.006185922495150944 1 0 Concrete_0
#add_dispersion_debye: 1 3.010007267468401 8.663325812708461e-10 Concrete_0
#box: 0 0 0 0.5 0.3 0.3 Concrete_0
#cylinder: 0.25 0 0.1903641857372006 0.25 0.3 0.1903641857372006 0.013888010719931749 pec
#python:
from user_libs.antennas import GSSI
GSSI.antenna_like_GSSI_1500(0.25, 0.15, 0.3, resolution=0.001)
#end python:
```

Figure 4.2: .in file

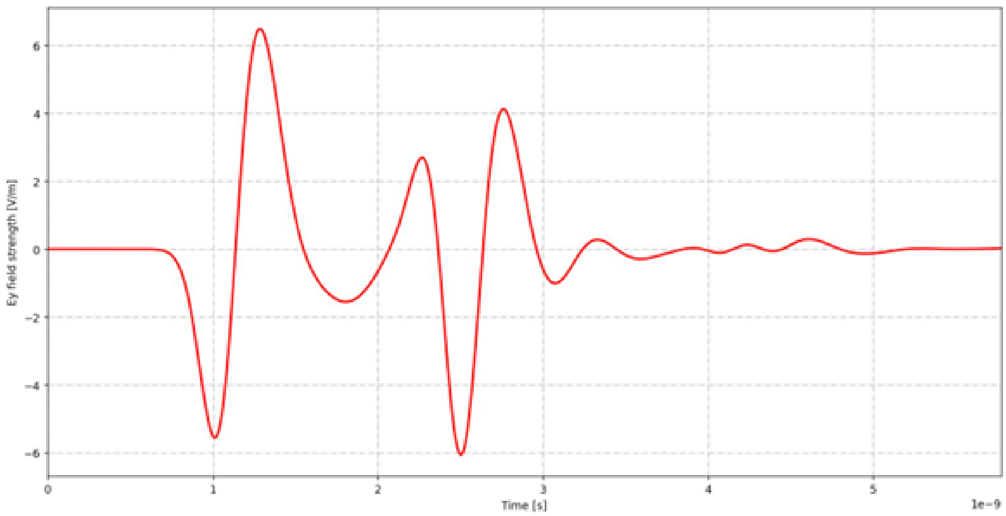

Figure 4.3: .out file

The dataset includes various configurations of rebars with diameters ranging from 6 mm to 24 mm, depths varying between 100 mm to 200 mm, and different moisture contents within the concrete. Each configuration consists of multiple A-scans, resulting in a diverse and extensive dataset. This data was crucial in training the ML-based forward solver, enabling it to accurately predict GPR responses in near real-time across different scenarios.

4.2 System Architecture

4.2.1 1.Data Ingestion and Preprocessing

- **Input Data Generation:**
  - The first step in the data ingestion process involved in generating the .in files, which served as the input for Ground Penetrating Radar (GPR) simulations. These files were carefully designed to model various subsurface scenarios, incorporating different values for rebar depth, radius and the percentage of water content in the concrete. Additionally, radar system parameters like the frequency of operation and pulse type were specified to create a realistic simulation environment. These configurations were essential for ensuring that the simulated radar responses would accurately reflect potential real-world scenarios.
- **Simulation with gprMax:**
  - Once the .in files were prepared, they were used as input for gprMax, a well-known simulation tool for modeling electromagnetic wave propagation through complex media. gprMax processed these input files to generate .out files, each containing a time-domain signal representing the radar's response to the subsurface conditions modeled in the corresponding .in file. Given the large number of simulations (2000 in total), significant computational resources were required. The simulations were run on a high-performance computing environment, leveraging parallel processing capabilities to manage the workload efficiently. This approach allowed for the timely generation of all required .out files.
- **Output Data Overview:**
  - The output of the gprMax simulations consisted of 2000 .out files, each representing a time-domain signal with 3000 data points. These signals captured the reflections and transmissions of the radar waves as they interacted with different subsurface layers and materials. The high-

resolution data provided a detailed view of the radar's response, which was crucial for subsequent data processing and analysis steps.

4.2.2 Data Preprocessing

- **Downsampling:**

  Given the high dimensionality of the time-domain signals, downsampling was a necessary step to reduce the data size while retaining essential information. The original signals, each with 3000 data points, were downsampled to 300 points. This process involved selecting every tenth data point from the original signal, thereby reducing the computational complexity without significantly affecting the overall signal characteristics. Downsampling was particularly important for preparing the data for machine learning algorithms, which often perform better with reduced input dimensions.

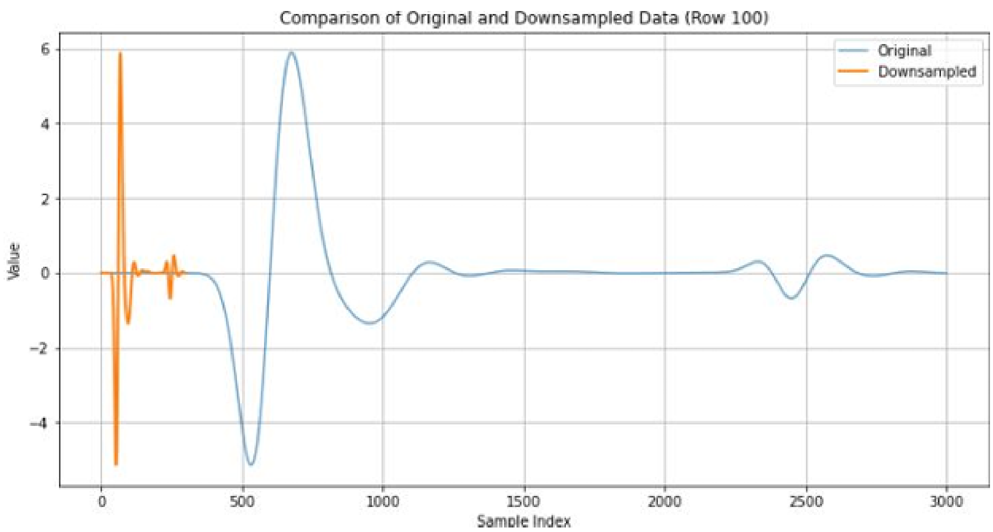

Figure 4.4: Comparison of downsampled and original waveform

- **Normalization:**

  In preparation for Principal Component Analysis (PCA), the downsampled data was normalized. Normalization involved adjusting the amplitude of the signals so that they all fell within a common scale. This step was essential to prevent any single signal from dominating the PCA results due to differences in magnitude. By normalizing the data, each signal was given equal importance, ensuring that the principal components reflected genuine patterns in the data rather than artifacts of varying signal strength.

Principal Component Analysis (PCA):

- PCA was applied to the normalized, downsampled data to further reduce its dimensionality while preserving the most significant features. The goal was to distill the original 300 data points per signal into a smaller set of principal components that captured the majority of the variance in the dataset. After performing PCA, 40 principal components were selected based on their cumulative contribution to the total variance. This reduction allowed for more efficient analysis while retaining the most critical information contained in the original signals. The selection of 40 components was determined by examining a scree plot, which showed the variance explained by each component, and choosing the number of components that captured a substantial portion of the total variance.

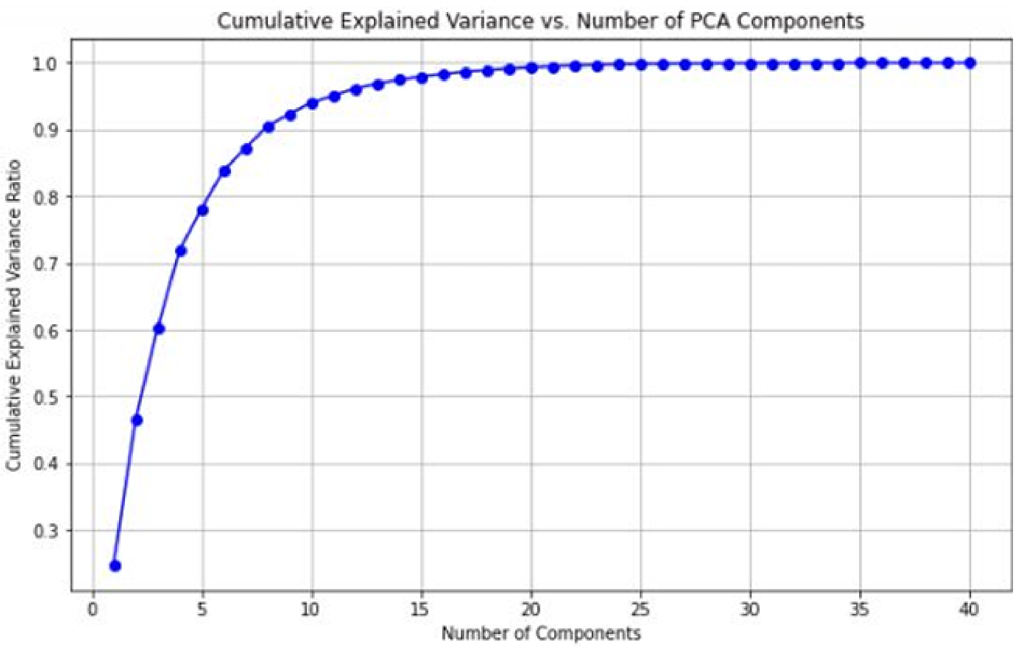

Figure 4.5: PCA Components

Data Splitting:

- The dataset was divided into distinct subsets for training, validation, and testing. This segmentation ensures that the model is trained on one portion of the data, validated on another, and tested on an entirely different subset, thereby preventing overfitting and ensuring generalizability.

4.2.3 Model Initialization and Training

- **Model Architecture:**

  The machine learning model developed for this project is a deep neural network specifically designed to predict subsurface properties from Ground Penetrating Radar (GPR) data. The architecture leverages the dimensionality-reduced features obtained through Principal Component Analysis (PCA) and is structured to effectively capture the complex, non-linear relationships inherent in GPR signals.

Ensemble Model

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 300)	1,200
dense_1 (Dense)	(None, 300)	90,300
dense_2 (Dense)	(None, 300)	90,300
dense_3 (Dense)	(None, 300)	90,300
dense_4 (Dense)	(None, 300)	90,300
dense_5 (Dense)	(None, 40)	12,040

Total params: 374,440 (1.43 MB)
Trainable params: 374,440 (1.43 MB)
Non-trainable params: 0 (0.00 B)

Figure 4.6: Ensemble Model

- **Input Layer:** The input layer of the model consists of three nodes, each corresponding to one of the key input parameters: Rebar Radius (R), Depth (D), and Moisture Content (MC). These parameters are vital for simulating

GPR signals, as they directly influence the electromagnetic response captured in the A-scan data. By feeding these parameters into the model, the network is set up to learn the dependencies between these physical characteristics and the output GPR signals.

- **Hidden Layers:**: Following the input layer, the model includes five hidden layers, each containing 300 neurons. These neurons are activated using the ReLU (Rectified Linear Unit) function, a widely-used activation function in deep learning due to its efficiency in overcoming the vanishing gradient problem. The ReLU function introduces non-linearity to the model, enabling it to learn complex relationships in the data. The deep architecture, characterized by these multiple hidden layers, allows the model to capture higher-level abstractions, making it more capable of accurately predicting the principal components of the GPR signals.

- **Output Layer:** The final layer in the model is the output layer, which consists of 40 neurons. Each neuron in this layer corresponds to one of the principal components derived from the Principal Component Analysis (PCA) of the A-scan data. The use of a linear activation function in the output layer ensures that the model's predictions are continuous and directly comparable to the actual PCA components. This design choice is essential for the model's role in accurately reconstructing the original GPR signals from the predicted components.

- **Training Process:** Training the model involves several critical steps, beginning with the division of the dataset into training, validation, and test sets. The training set comprises 60% of the data, which the model uses to learn; the validation set accounts for 20% of the data, helping to tune the model and prevent overfitting; and the test set, also 20%, is reserved for evaluating the model's final performance. The Adam optimizer, known for its adaptability and efficiency, is employed with an initial learning rate of 0.001 and a learning rate decay of 1e-7. The model is trained to minimize the Mean Squared Error (MSE), a common loss function for regression tasks, which measures the average squared differences between predicted and actual values.

Ensemble Averaging: To further enhance the model's predictive accuracy, an ensemble averaging technique is implemented. This involves training 40 separate models, each initialized with different weights, and then averaging their predictions to produce the final output. Ensemble methods are known to improve model robustness by reducing the impact of individual model biases and variances. This approach is particularly effective in scenarios where the data is complex and the relationships between variables are highly non-linear, as is the case in GPR forward modeling.

Chapter 5

SYSTEM REQUIREMENTS

5.1 Software Requirements

5.1.1 Python:

Python 3.11 is a powerful tool for various development projects due to its improved perfor- mance, new features, robust community support, and adaptability.Python is a well-liked, easy-to-learn programming language with a large ecosystem that makes it suitable for beginners and programmers alike. Because of its simple syntax that is easy to under- stand and use, developers from a variety of fields, like web development, data science, automation, and artificial intelligence, are drawn to it. Python's dynamic typing allows for expressive and flexible programming, while its interpreted nature facilitates quick de- velopment and debugging. Python has a wealth of libraries and frameworks, including TensorFlow, PyTorch, NumPy, and Pandas, that enable developers to work on a variety of applications, from machine learning to scientific computing. Python is a vital tool for contemporary software development, encouraging creativity and teamwork with the help of a thriving community.

5.1.2 Google Colab

Google Colab is a hosted Python Notebook service that offers no setup requirements and and provides free access to computing resources, including GPUs and TPUs. .For Python code execution, Google Colab, also known as Google Colaboratory, offers a free cloud computing environment that is ideal for machine learning and data science projects. Because of its interaction with Google Drive, users may access files and datasets with ease. Additionally, its browser-based interface, which is similar to Jupyter Notebooks, provides an easy-to-use environment for writing and running code. Free GPU and TPU resources are one of Colab's best advantages; they allow deep learning models to be trained more quickly without the need for specialist hardware. Additionally, Colab makes collaboration easier by enabling numerous users to collaborate on the same notebook at once, which makes it perfect for group projects and educational uses. Preinstalled libraries and the option to add more dependencies make Colab a development process streamliner that promotes experimentation and sharing among team members.

Libraries and Frameworks:

- **Torch:** PyTorch is a deep learning library that supports tensor computations. It is essential for training and utilizing the BART model.
- **Pandas:** This library is used for data manipulation and analysis, particularly for handling datasets.
- **Datasets:** The Hugging Face Datasets library provides efficient data handling and access to a wide range of datasets.
- **Evaluate:** This library is used to compute various evaluation metrics, including ROUGE scores for summarization tasks.

5.2 Hardware Requirements

- Processor: A multi-core CPU (e.g., Intel Core i5)
- Memory (RAM): 8GB RAM to handle large datasets and deep learning model operations effectively.
- GPU (Optional but Recommended): GPU with CUDA support (NVIDIA GeForce GTX or RTX series) for accelerated training of deep learning models.

Chapter 6

RESULTS

The model demonstrates solid predictive performance, as indicated by its metrics. With a Mean Squared Error (MSE) of 0.4101, the model maintains a relatively low average error, reflecting its accuracy in predicting outcomes. The Root Mean Squared Error (RMSE) of 0.6404 suggests that the model's predictions are, on average, close to the actual values, showcasing its reliability in practical applications. Furthermore, the R^2 score of 0.5956 reveals that the model successfully explains approximately 59.56% of the variance in the target variable, highlighting its effectiveness in capturing the underlying patterns in the data. Overall, these results underscore the model's capability and robustness in predictive tasks.

We also checked the performance of another Neural Network architecture as part of experimentation. For this model, we got an MSE of 0.73.

Fig. 6.1 and Fig. 6.2 show the visual comparison of predicted signal and ground truth from ensemble model and NN-based experimentation model respectively.

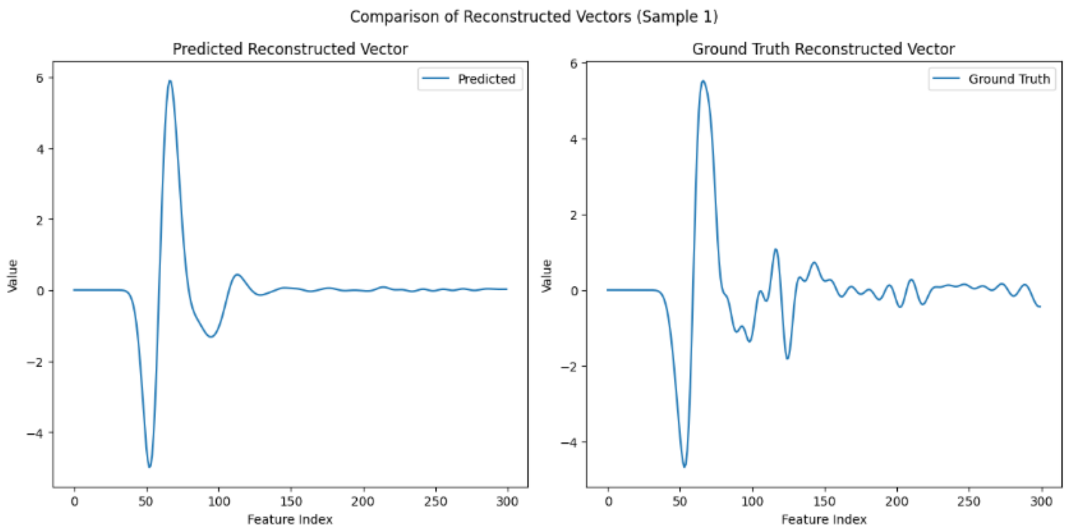

Figure 6.1: A visual comparison of predicted signal (generated using Ensemble model) and ground truth.

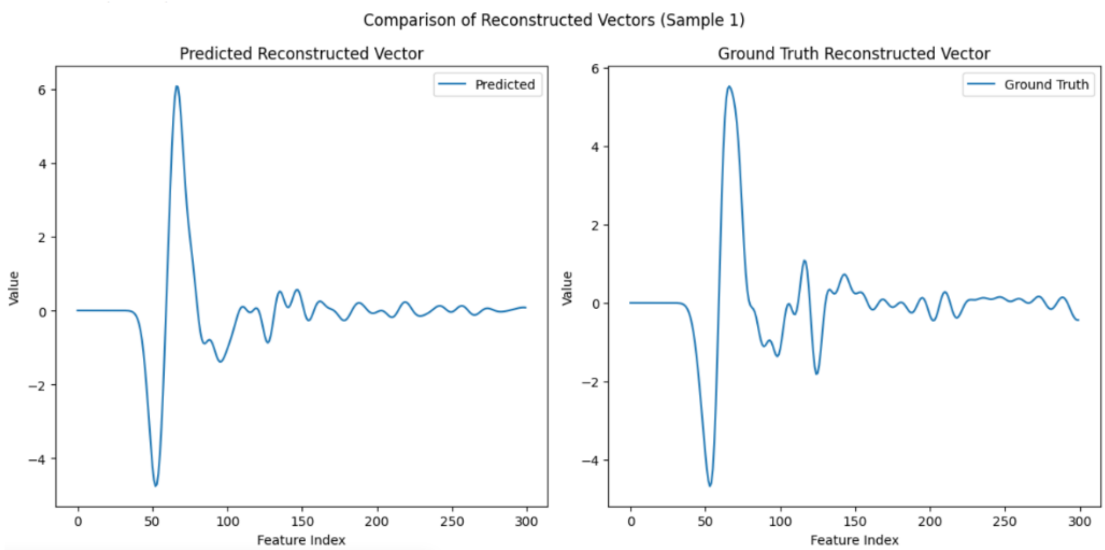

Figure 6.2: A visual comparison of predicted signal (generated using NN model) and ground truth.

Chapter 7

Conclusion and Future Scope

The development of the machine learning-based forward solver for Ground Penetrating Radar (GPR) has shown promising results in accurately predicting the complex interactions between the GPR antenna, the target, and the surrounding materials. The model effectively handles the computational challenges typically associated with traditional Finite-Difference Time-Domain (FDTD) methods, providing near real-time predictions with a high degree of accuracy. The combination of principal component analysis (PCA) and a deep neural network architecture has allowed for efficient data processing and robust performance. The model's ability to generalize across various scenarios, such as estimating the depth, diameter, and moisture content of rebars within concrete, marks a significant advancement in GPR-based non-destructive testing. The strong performance metrics, including a low Mean Squared Error (MSE) and a favorable R^2 score, underscore the model's reliability and its potential for practical applications in infrastructure assessment and geophysical investigations.

Despite the promising results, there is room for improvement. Visibly, there is a mismatch between the predicted and ground truth in the reflected part of the A-scans. To address this, the model can be enhanced by implementing the more advanced architecture discussed in the referenced paper [3]. Additionally, improving the dataset, possibly by increasing the diversity of scenarios or refining the quality of the training data, could lead to better model performance. Further exploration into alternative ML techniques or hyperparameter tuning could also yield better results, making this approach even more effective for real-world GPR applications

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