Software Proposal Document for Detecting Constructions' Distortions using Ground Penetration Radar

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Proposal Version	Date	Reason for Change
1.0	21-October-2020	Proposal First version's specifications are defined
2.0	14-November-2020	Change of Project's Idea

GitHub: https://github.com/DominyRonin/GPR-DDS

Abstract

Every day buildings are becoming more exposed to fall apart due to many factors like bad construction design, extraordinary loads and Soil liquefaction which if not detected at the right time may cost too many innocent lives. The main idea of the proposed project is identifying defects in constructions, their types and the reason behind them in order to determine the condition of the building so that the maintenance and repairing process become more effective, no dangerous situations are faced and the loss is not too costly. Image processing and machine learning techniques will be used to differentiate between many classes of the defects, classify and detect common defects in the concrete using CNN-Cam and VGG-16 algorithms.

1 Introduction

1.1 Background

A large Number of constructed buildings are in increase daily in worldwide especially in China, India United state [1]as they are considered as top three countries as earlier before 20th century people suffered from the buildings defects as it end horribly as the owners consider that their buildings are durable[**josephson˙larsson˙1970**] as it lasts for a long time as the structure segments break down at different rates and degrees depending on the plan, materials and techniques for development, nature of workmanship, ecological conditions and the employments of the structure , Imperfections result from the reformist crumbling of the different segments that make up a structure. Deformities happen through the activity of one or a blend of neutral factors, and those problems ended with horrible disasters till the mid of 20th century as a lot of scientists discovered that most of the common mistakes that happen in the building structures are human mistake and they also said that the neutral factors doesn't effect that much on the structure of the buildings like the human mistake for example , Argyris and Schön in 1978 they analysed more than 2000 document error from building and civil engineering projects , The purpose was to understand how defects occurred and most of the defects were human mistake[2] , At the end of 20Th century Australia published the first building standard inspector in 1997 and it was one of the first solutions but it couldn't be the perfect solution as it was only detecting the visible defects like cracks and stains but no one had any other solution until 2007 the inspectors started using GPR(Ground Penetration Radar)[3] images to identify the defects that cant be seen it worked for a long term but wasn't accurate enough as it depended on the experience of the inspector to identify if its considered as defect or not and it costed a lot of money and time to identify and study the defects that cant be seen and in this period the disaster might happen , and by the time the detecting the defects became easier as algorithms became provided that helped them in detecting the errors but till now there isn't any accurate method made that can detect the percentage of the defects correctly [4] , now we combined those methods that had been used till now to provide an easy and accurate way by using both of machine learning and image processing.

Figure 1: Example of a defect

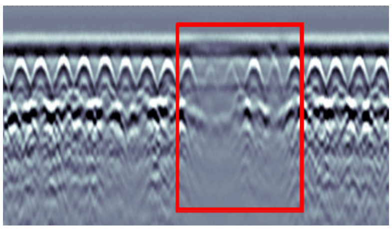


Figure 2: Example of a defect IN GPR

1.2 Motivation

1.2.1 Academic

Over the past years, different approaches have been proposed on the way designing concrete structures like building, Bridges and dams. With complex designs of buildings and the use of new materials like steel, concrete constructions' durability has been affected due to lack of correct monitoring procedures and care. Mix design, mechanical overload, chemical attack, poor construction, mechanical overloading and environmental exposure are some factors that affects concrete strength and durability[5]. Those factors affect concrete and cause some defects; voids, corrosion, cracks, water leakage, deterioration. Those defects cause sever damage to the integrity of concrete causing building and bridges to fall leading to a serious amounts of injuries and an increase in death rates. According to statistics[6].

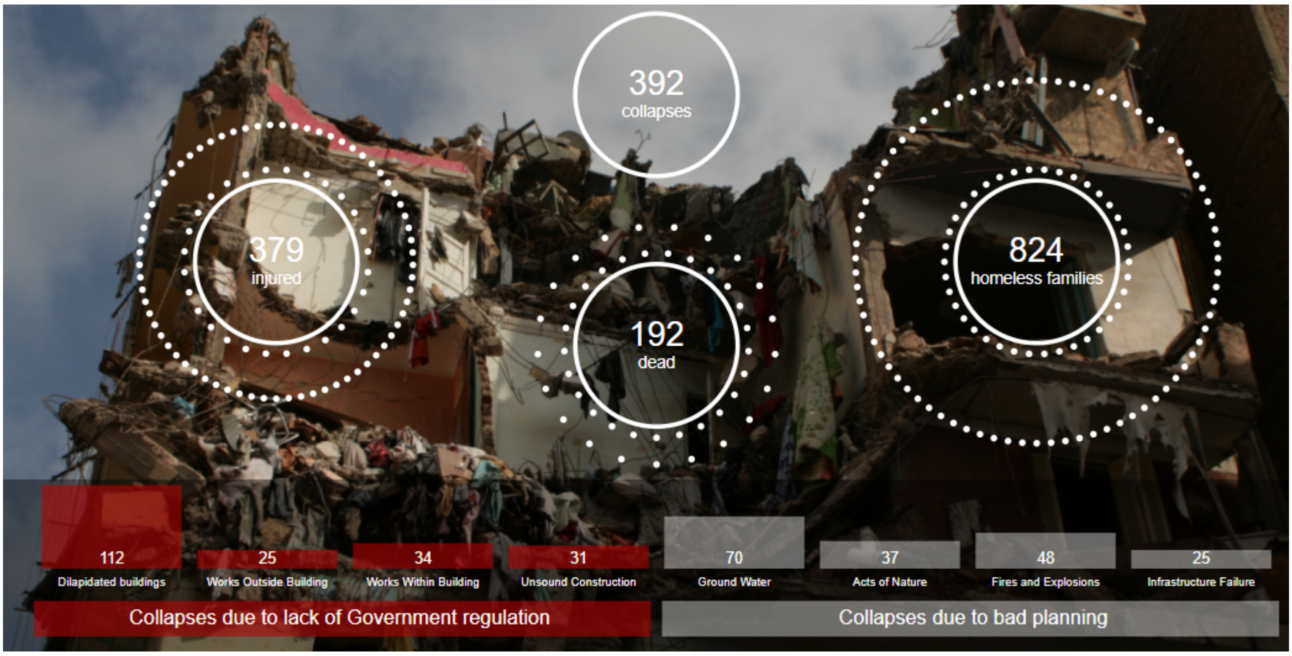


Figure 3: Statistics

1.2.2 Business

According to statistics[7] people that want to hire an inspector those days are paying a lot as most of the new buyers need to check if there is any thing wrong with the concrete of the building or an owner of a building want to check about the building infrastructure state they wait for at least 3 months to give them the final results and its not accurate as they neglect some unknown errors , by using our program it will :

- Help in Saving a lot of money that is being spent on the constructions companies that works on detecting the the defects.
- Help in increasing the accuracy of the results as it will save time and effort in the detection process
- Help in reducing the time of that is taken to produce the results of the scanning process

1.3 Problem Statement

The problem that the project aims to detect concrete constructions' defects and their types before facing any dangerous situation, that will help find out the problem before the loss is too costly. This is a crucial thing to address in this project and the key problems we face can be summarized in the following:

- Detecting Concrete's defects in early stages by training the GPR images using machine learning and image processing (Histogram).
- Early detection will help in notifying the user if the building in bad situation and need to immediately evacuate or the defect can be partial and not that dangerous.

2 Project Description

This project helps in the detection and classification of the unseen defects in the concrete buildings and its infrastructure by a Ground Penetrating Radar(GPR) B-scan image,this system will help in decreasing the collapsing of the building by detecting the defect of in the concrete early stages , which will help in fixing the defect,also the goal is to reach a high accuracy for the detection to be more optimized that will help in decreasing the disasters of the collapsed buildings.

2.1 Objectives

Our objective is to build a desktop application that can detect the defects in the concrete or walls as it will help in identifying the type of the defect as if it is (voids or fractures)[8] and notify the user if its suitable to deal with or not , it will also help in reducing the percentage of the collapsed buildings by reaching the highest accurate percentage which will exceed 95% at the detection process, moreover it will save time and effort for the inspectors in detecting the defects and it will be delivered by the end of they year.

2.2 Scope

In the proposed system we will be able to state the difference between many classes of different mediums other than concrete and if the inserted image is in fact concrete, the system will be able to classify and detect its common defects using our trained model also it will detect moisture using image processing. Our system shall:-

- Sate the difference between many negative classes (which aren't concrete like walls and other mediums) and locate the positive images (concrete).
- Classify and detect common defects like voids, fractures and cracks .
- Detect moisture level using image processing techniques.

2.3 Project Overview

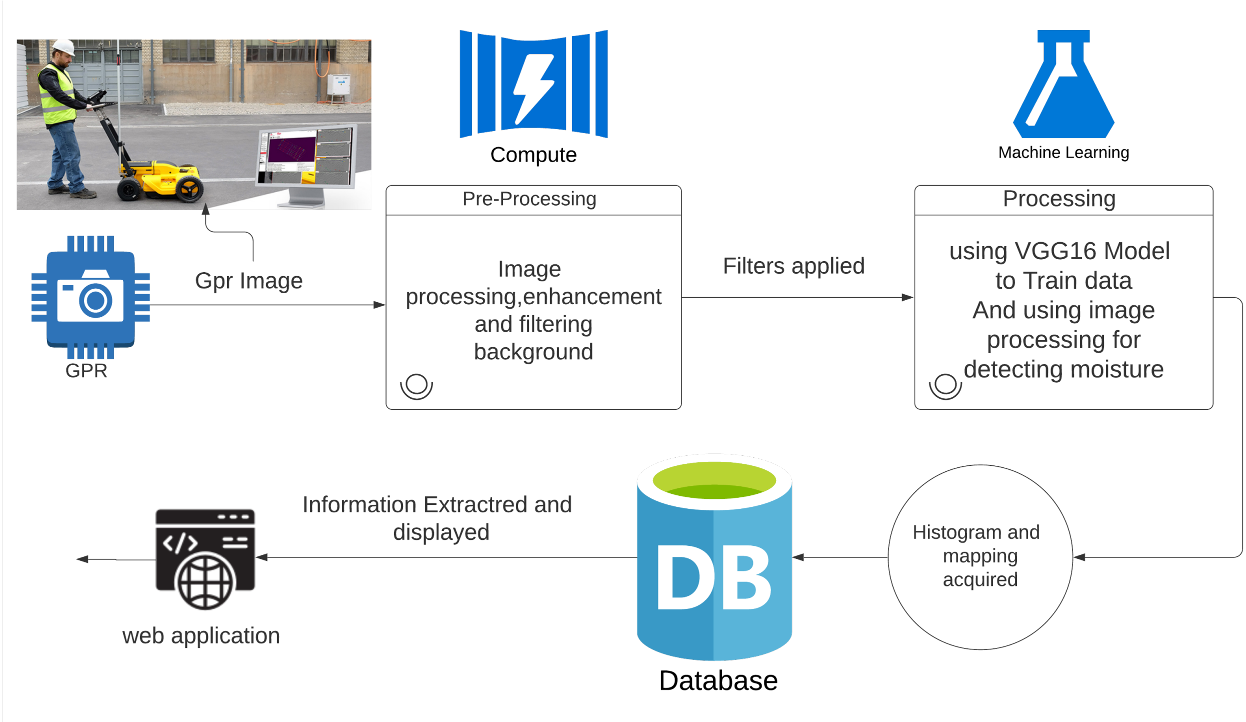


Figure 4: System Overview

Our system will be classifying and detecting concrete defects using images captured by a Ground Penetrating Radar(GPR), we provide a detection process that starts by taking a photo using GPR(Ground-penetrating radar) [9] which undergoes the pre-processing phase that includes resizing of images, normalization and enhancement and image segmentation. Machine learning process as the it will start using the required algorithms like (VGG-16[10] and CNN-CAM [11]) to start optimizing the image as it will be compared with the defects in the database,.In the end, it will be saved to the database and a histogram/report will be created about the image, information is then displayed in a user-friendly web application.

2.4 Stakeholder

2.4.1 Internal

Member	Job
Mohamed Mahmoud	Team Leader and back-end developer
Adham Mohamed	Document writing & front end
Ahmad Mostafa	Researches,Front-end & Back-end
Mohamed saed	Researches & Back-end

3 Similar System

3.1 Academic

Jiheng Liu, Zemin Zhou and Xinwu Zeng [12] used Multi-static active sonar to detect underground targets. they used 2 machine learning methods for recognition and classification of extracted features; Support Vector Machine (SVM) and Random Forest (RF). For experimenting, they used 6 different targets of different shapes, sizes and material. Finally, they concluded that both SVM and RF methods are accurate and fast. Recognition rate was above 90% under certain conditions; small training set, test set numbers and high SNR.

Yoojeong Seo, Beomhui Jang and Sungbin [13] Im used 2 machine learning techniques on the data received by horizontal array sonar to estimate the direction of moving targets under water. They used cross-spectral density matrix (CSDM) for feature extraction, quadratic SVM for optimization and classification and Bagging tree for model generalization and lowering the correlation. They studied the relationship between the number of sensors used by the model and the model performance and concluded that as the number of used sensors increase, the accuracy increases as shown in figure 5.

No. of sensors	Quadratic SVM (%)	Bagging tree (%)
3	49.5	55.2
5	54.4	61.2
7	55.1	65.7
9	56.7	70.5
11	59.8	76.5
13	75.0	86.7

Figure 5: Results

Zhong Qu et al [14] proposed an algorithm to detect cracks in concrete pavement using deep learning techniques. They used modified LeNet-5 network for crack classification and improved VGG16 network for crack detection and extraction. They used The Algorithm of Cross-Entropy Loss for calculating the distance between predicted and actual output distribution probabilities. Finally, they compared the results from their proposed method with 3 different methods (VGG16, U-net, Percolation) on different Data sets, the proposed method achieved the highest results in terms of precision, recall and F1 as shown in tables 1, 2 and 3.

Methods	precision	Recall	F1	FPS
VGG16	0.570	0.740	0.644	30
U-NET	0.855	0.882	0.868	6
percolation	0.582	0.447	0.505	0.05
Ours	0.889	0.903	0.896	30

Table 1: Data set 1

Methods	precision	Recall	F1	FPS
VGG16	0.305	0.538	0.389	30
U-NET	0.760	0.694	0.726	6
percolation	0.121	0.631	0.203	0.05
Ours	0.829	0.966	0.892	30

Table 2: Data set 2

Methods	precision	Recall	F1	FPS
VGG16	0.407	0.341	0.371	30
U-NET	0.848	0.851	0.849	6
percolation	0.453	0.326	0.379	0.05
Ours	0.912	0.891	0.901	30

Table 3: Data set 3

Yan Song et al[15] proposed a Simple Ensemble Extreme Learning Machine based of Markov Random Fields (SE-ELM-MRF) for segmentation of sidescan sonar Images. they used SE-ELM for pixel classification of sidescan sonar images and calculating the initialization parameter for MRF which formt SE-ELM-MRF. The results were compared with different methods; k-means, MRF, ELM, ELM-MRF, kernel-based ELM(KELM), KELM-MRF, SVM, SVM-MRF, CNN, CNN-MRF and SE-ELM. the proposed method proved to have the highest accuracy with low testing time as shown in figures 6 and 7 .

	Data Sets for testing	ELM and MRF	KELM and MRF	SVM and MRF	CNN and MRF	SE-ELM and MRF
Testing accuracy	Data Set 4	90.15%	86.36%	90.02%	90.13%	91.72%
	Data Set 5	89.30%	88.41%	89.36%	89.50%	91.99%
	Data Set 6	89.75%	86.52%	90.14%	90.17%	91.88%
	Data Set 7	87.85%	82.16%	88.60%	88.68%	89.90%
	Data Set 8	89.48%	81.16%	89.95%	89.94%	91.53%
	Data Set 9	98.13%	90.64%	97.88%	97.80%	98.52%
Testing time (seconds)	Data Set 4	1.07	74.19	88.65	1.65	1.67
	Data Set 5	1.06	66.99	86.30	1.48	1.56
	Data Set 6	1.46	111.08	101.63	2.06	2.11
	Data Set 7	2.64	285.04	333.86	4.66	4.82
	Data Set 8	5.02	657.30	360.92	10.63	11.59
	Data Set 9	1.11	97.64	164.33	1.91	1.95

Figure 6: Accuracy results

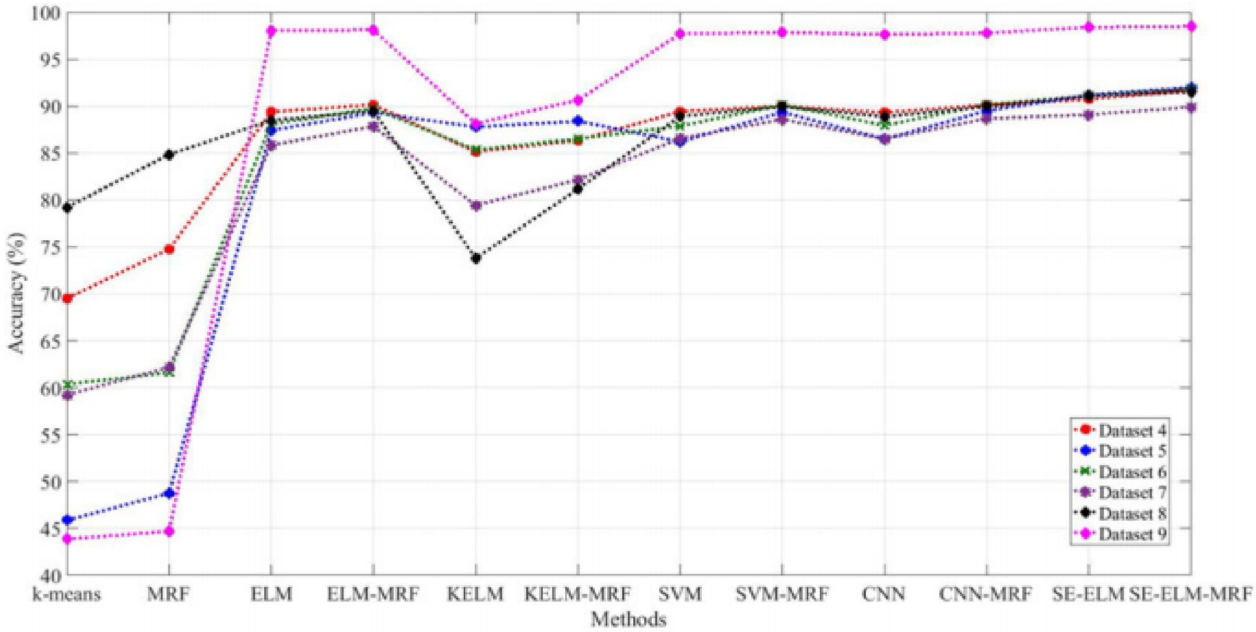


Figure 7: Graph representation for methods' accuracy

Ke Tan, Xiaonan Xu and Hongyu Bian [16] used the normal distribution transform (NDT) algorithm of image matching in sonar image processing. They used some images processing techniques for noise reduction, the mean and median methods proved to be better in terms of time, PSNR and MSE. They selected the Otsu method for image segmentation. Finally, they chose the Otsu and median methods as the most appropriate algorithm for pre-processing.

Hao Wang [17] used deep learning method to build a system that recognize and classify garbage. They used the CNN-VGG16 model to identify and classify domestic garbage into kitchen waste, recyclable garbage, hazardous garbage or other garbage. They used 4 image pre-processing techniques for image enhancement using OpenCV library; Gaussian blur, image binarization, positioning and selection and Crop. the proposed method in this paper has achieved an accuracy of 75.6% which still needs to be improved.

Hussam Qassim, Abhishek Verma and David Feinzimer[18] proposed a deep learning model for big data image recognition. they proposed a Residual Squeeze VGG16 network Architecture which sums up 3 popular deep learning methods; CNN-Vgg16, Residual Learning and SqueezeNet. they used a data set of 1.8M training images created by MIT Computer Science and Artificial Intelligence Laboratory. the proposed method proved to be 23.86% faster and 88.6% smaller in size than VGG16 with a time of 2 days and 19 hours : 3 days and 16 hours and a size of 1.23GB : 10.6GB.

Nontawat Pattanajak and Hossein Malekmohamadi [19] reinvented 2 models from VGG16 with and without Vatch Normalization (BN) to improve a 3D CNN model. they used UCF101 dataset for Human Activity Recognition which contains 13,320 video clips. the 2D CNN-VGG16 model acheived an accuracy of 89.3% on VOC-2012 dataset (images) because the VGG16 original model is a 2D CNN model that only supports images. After building the 3D CNN-VGG16 model and comparing the with and without BN, the results show the accuracy of the 3D CNN-VGG16 with BN is 91.2% as shown in table 4.

Leilei Jin, Hong Liang and Changsheng Yang [20]proposed a method for accurate underwater target detection using Deep Convolutional Neural Networks (DCNNs) and forward-looking sonar-Echoscope. They tests their method on a data set of 9 classes (2,915 images) and compared the results of their proposed method to 4 different classifiers and 2 DNNs; KNN_raw_pixel, MLP_raw_pixel, NN_HOG, SVM_HOG, AlexNet and GoogleNet with accuracies of 72.0%, 89.3%, 91.4%, 92.7%, 94.1% and 97.0%. their method (EchoNet) reached an accuracy of 97.3% as shown in figure 8.

Model	Accuracy
Two - Stream I3D ,Imagnet + Kinetics pre-training	98%
ST-ResNet+IDT	94.6%
Temporal Segment Network	94.2%
Two-Stream Fusion +IDT	93.5%
TDD+IDT	91.5%
3D CNN reinvented from VGG16 with BN	91.2%
C3D ensemble +IDT Sport 1M pre-training	90.1%
Dynamic Image Network+IDT	89.1%
TWO-STREAM	88.0%
IDT	86.4%

Table 4: Accuracy results on UCF101 Dataset

Method	Accuracy	Inference time per image (ms)
KNN_raw_pixel	72.0%	341.2
MLP_raw_pixel	89.3%	1.1
NN_HOG	91.4%	311.4
SVM_HOG	92.7%	133.7
AlexNet	94.1%	73.1
GoogLeNet	97.0%	186.9
EchoNet	97.3%	60.6

Figure 8: Accuracy results

Kushal Virupakshappa and Erdal Oruklu [21] used 3 unsupervised machine learning algorithms to detect ultrasonic A-Scan flaws; K-Means clustering, Gaussian Mixture Modeling and Mean Shift. For implementation, their software pipeline includes the processing of A-Scans and obtaining of Low-Pass(LL) component of the Discrete Wavelet Transform decomposition. Gaussian Mixture Modeling achieved the highest accuracy compared to the other 2 algorithms with an accuracy of 93%.

3.2 Business Applications

Application	Methods	Type of Data	Accuracy
Analysis of Functional NeuroImages (AFNI)	Slice timing, Motion correction,Smoothing ,Mask & Scale	Gray Scale images	97.7%
Analyze	SPM	magnetic resonance imaging, computed tomography and positron emission tomography.	
FMRIB	FEAT,MELODIC,FLOBS & SMM	Images	96.26%
CVIPtools	Arithmetic and logic, Conversion of image files, Edge/Line detection, Histogram, Mapping, Morphological,	TIFF, PNG, GIF, JPEG, BMP,	71.43%
KNIME	JFreeChart, ImageJ, and the Chemistry Development Kit.	doc, ppt, xls, pdf	92.3%

4 What is new in the Proposed Project?

The new in the proposed project is helping in checking the place as you can identify the defect in the concrete more easily using the provided program and it will although notify you how dangerous it is and the type of the defect, it will also help in saving money , time and the accuracy will be more accurate .

5 Proof of concept

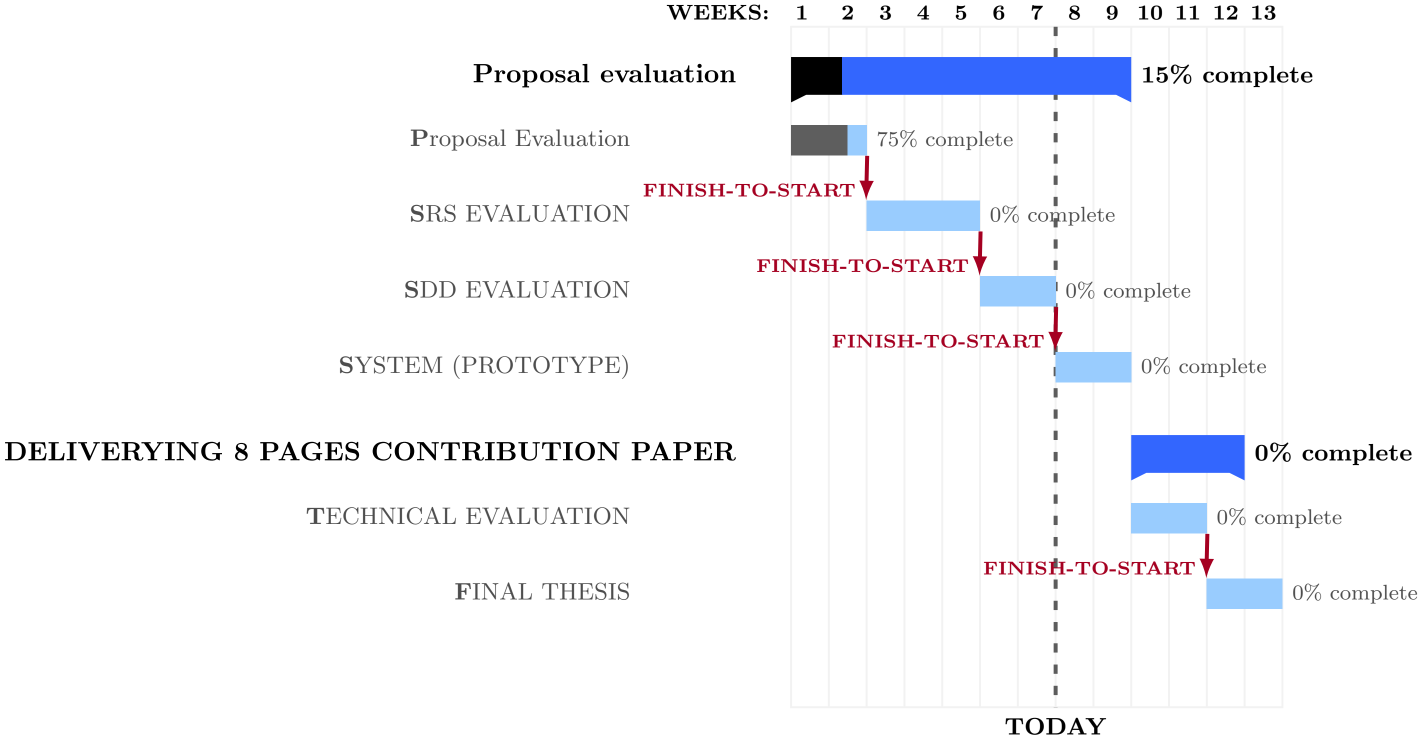
We was able to detect the defects in GPR B-Scan images using histogram , was even able to segment the defects in some the samples using filters and get the histogram for over then 8000 images to get the idle shape of GPR image and you can view the results at For further references see https://youtu.be/LKHWRzIJXU4

6 Project Management and Deliverables

6.1 Deliverables

- Q1: What will the project produce? (program, reports, etc.)
- =¿Program will produce diagrams(Histograms) and info will be extracted from them and the report will be generated to the user simply .
- Describe in brief detail the features of each of the deliverables.
- =¿ An image will be captured and go through image processing techniques(segmentation, filters and enhancement) and deep learning method for classification to produce a diagram displaying defects or Defect info. in the building.
- Separate deliverables into milestones (based on MIU graduation project calendar)
  - 1-Images Capturing using GPR.
  - 2-image segmentation achieved .
  - 3-Filtering and enhancement.
  - 4- image's histograms created.
  - 5-deep learning classifications achieved.
  - 6-simple report generated for user.

6.2 Tasks and Time Plan



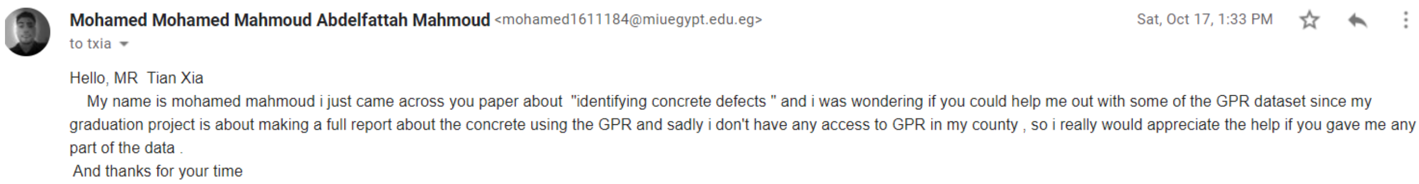
6.3 Budget and Resource Costs

- The only resource needed is GPR Camera which retrieves B-scan images needed in the project because of the length of the rays that's sent from the GPR.

7 Supportive Documents

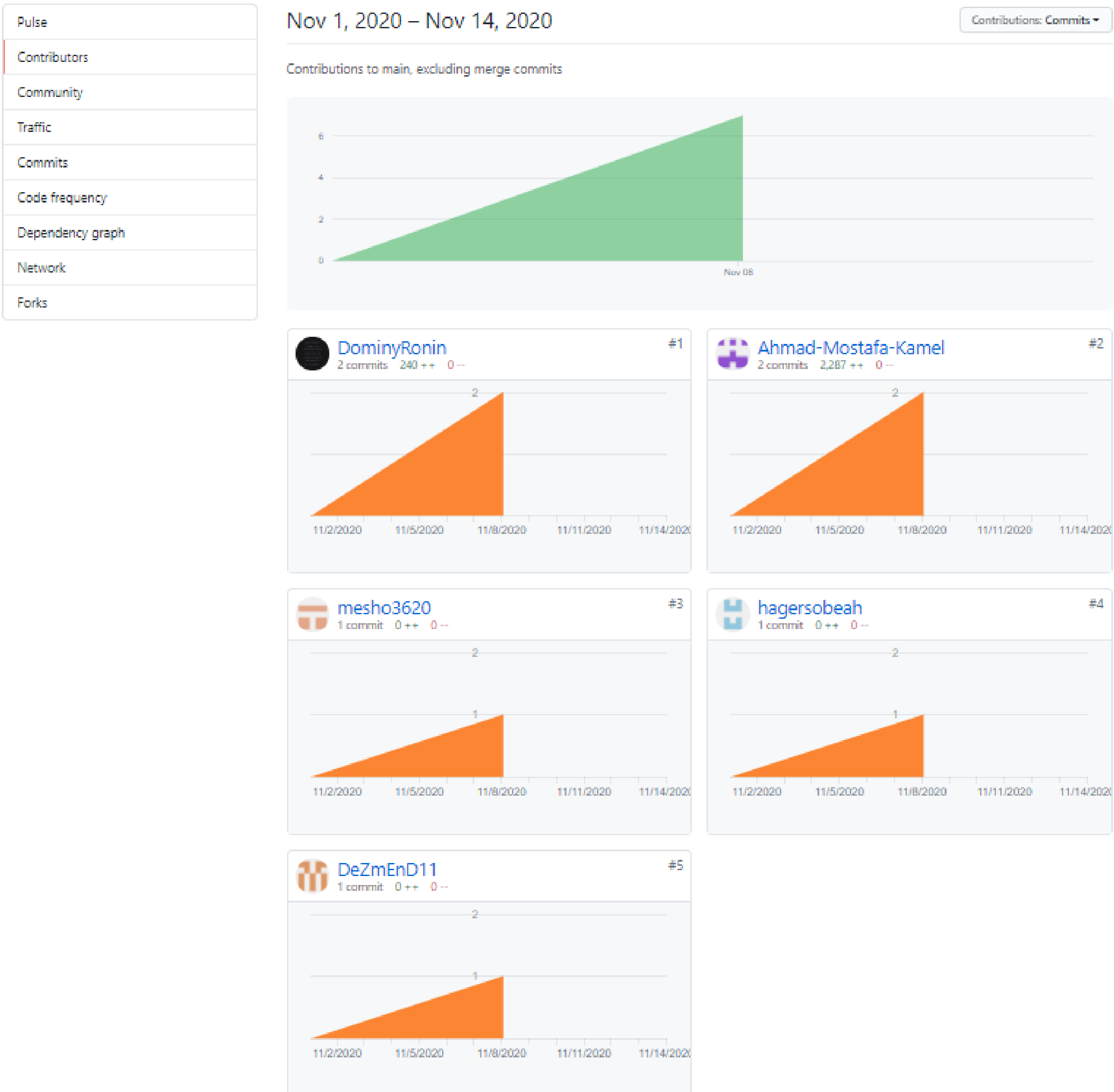
Add sections covering one or more of the following:

- The Data set was collected using transmission and reception of 10 MHz–2.6 GHz electromagnetic waves into the ground `https://github.com/PouriaAI/GPR-Detection`
- Contact documents.
- users/survey.
- Contacting authors


Mohamed Mohamed Mahmoud Abdelfattah Mahmoud <mohamed1611184@miuegypt.edu.eg> Sat, Oct 17, 1:33 PM
to txia

Hello, MR Tian Xia
My name is mohamed mahmoud i just came across you paper about "identifying concrete defects " and i was wondering if you could help me out with some of the GPR dataset since my graduation project is about making a full report about the concrete using the GPR and sadly i don't have any access to GPR in my county , so i really would appreciate the help if you gave me any part of the data .
And thanks for your time

8 The GitHub repository



https://github.com/DominyRonin/GPR-DDS

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