成都理工大學中英合作办学
CDUT Sino-British Collaborative Education

OXFORD BROOKES UNIVERSITY

# UNDERGRADUATE PROJECT PROPOSAL

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|---|---|
| **Project Title:** | **The identification of defects in underground pipes based on deep learning** |
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| **Module Name:** | **Project** |
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# 1 Introduction

## 1.1 Background

The number of pipelines put into use increases year by year. The United States has over 800,000 miles of public pipes and 500,000 miles of private pipes[1].And as the years of use increase, pipelines become deformed, corroded, leaky and other defects, causing problems such as ground collapse, industrial drainage pollution exceeding standards. Nowadays, closed-circuit television (CCTV) robots are mainly used to detect pipeline defects, however, which are time-consuming, inefficient, poorly accurate, require a large amount of personnel, and have high inspection costs. According to the U.S. Environmental Protection Agency (EPA), the treatment of pipe defects costs municipalities $2 to $5 per thousand gallons of sewage[2].

The advent of convolutional neural networks (CNN) in deep learning has led to breakthroughs in artificial intelligence, with CNN helping to extract more abstract features from raw data. Popular convolutional neural networks include Visual Geometry Group Network (VGG), Residual Neural Network (ResNet) and Long Short-Term Memory (LSTM) have been used with great success in image recognition and have been applied to a range of scenarios such as face recognition[3]. Meijer et al. showed that sewer image defects can be classified by convolutional neural networks to reduce human labor by more than 50%[4]. Therefore, it is beneficial to apply the technology to the identification of pipeline defects, and the new deep learning algorithm will be expected to promote the intelligence of underground pipeline defect identification and improve the efficiency as well as the accuracy of automatic detection of pipeline defects and have great promotion and application value in the identification of pipeline defects.

## 1.2 Aim

This project study the application of deep learning technology in identifying underground pipeline defect and the problem of low intelligence of underground pipeline defect detection, furthermore, apply deep learning in accurately identifying the defect category of pipeline automatically.

## 1.3 Objectives

To accomplish real-time intelligent defect identification for pipelines, the objectives of this project are:

- Collection of inspection videos of the pipeline and pre-processing of the training dataset
- Construct deep learning models and complete training and testing
- Change model parameters and structure and re-evaluate
- Core algorithms for intelligent pipe network identification projects using the best models

## 1.4 Product Overview

### 1.4.1 Scope

In this project, for the problem of low intelligence of underground pipeline defect detection, by constructing a deep learning-based neural network defect recognition model to complete real-time intelligent identification of underground pipes.

### 1.4.2 Audience

This project will reduce the degree of manual involvement, guarantee the safe operation of municipal pipelines, and reduce the huge economic losses caused by hidden dangers such as road collapse.

# 2 Background Review

## 2.1 Summary of existing approaches

### 2.1.1 Conventional methods

The current method of pipe network inspection is closed-circuit television (CCTV) robots for video filming followed by artificial detection of pipe defects. Firstly, the robot is remotely controlled by outside personnel to crawl inside the pipeline to take video of the pipeline, and then the professional staff watch the video, interpret the pipeline defects, and complete the pipeline assessment and industry report. Studies have shown that: (i) due to the lack of measurement software (ii) the quantification levels of standard methods are not uniform, and (iii) the manual interpretation of video is not qualified, so the CCTV report is inaccurate[5].

### 2.1.2 Deep learning methods

Hassan, S.I. et al.[6] and Mario A. et al.[7] have studied using convolutional neural network (CNN) for defect recognition of pipe defect images from CCTV videos and achieved better experimental results. However, the model can only recognize a single model when there are multiple defect categories in the image, and in addition, the method cannot accurately recognize and classify when the features of both the defective and non-defective regions of the pipe in the CCTV video are show diversity and have a complex environment; Cheng, J.C.P and Wang, M.[8] used the convolutional neural network Faster R-CNN for CCTV sewer defect images for automatic recognition and stated that deeper networks with more convolutional layers can extract image features more accurately and improve accuracy, and that training the model with a larger dataset can optimize the model. Target detection is mainly divided into two kinds of algorithms are One Stage and Two Stage, where One Stage represents the main algorithms such as Faster R-CNN[9] etc. Moreover, Lin et al.[10] proposed using feature pyramid networks (FPN) to fuse the high resolution of low-level features with the high semantic information of high-level features to achieve better results in target detection, and then ResNeXt proposed by Xie et al.[11] investigated a parallel stacking of blocks with the same topology instead of the original ResNet of three-layer convolutional block. For Two Stage algorithm that representatives are YOLO series, such as YOLOv7[13] which fuse YOLOv5 and YOLOX and the latest target detection algorithm tricks such as E-ELAN, Auxiliary Head, etc. Additionally, Leng et al.[13] propose a framework called “PolyLoss” to easily adjust the loss function according to the target task and dataset.

# 3 Methodology

## 3.1 Approach

Compared with the traditional underground pipeline defect identification, this paper study the real-time intelligent identification algorithm for the problem of real-time identification of underground pipeline defects. By improving, adjusting parameters of YOLOv7 and evaluating the effectiveness based on metrics, then analyze whether this algorithm can intelligently identify pipeline defects faster and more accurately in real time. The flow chart is shown in 3-1.

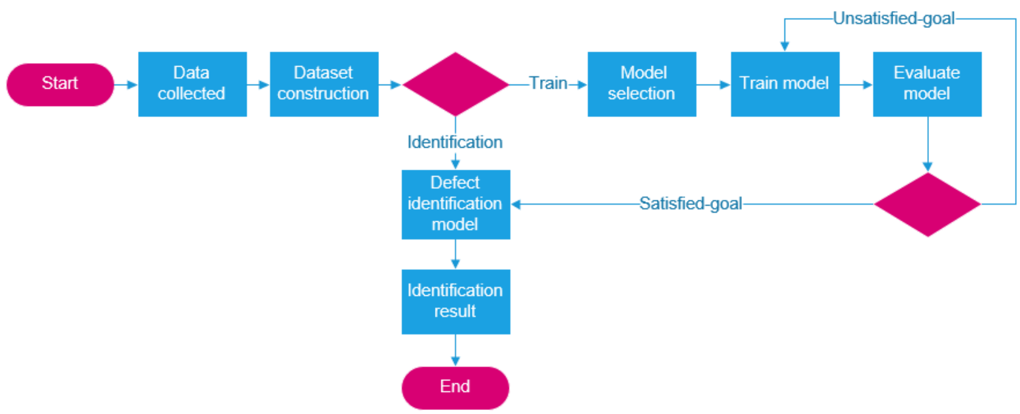


Figure 3-1 The flow chart of Pipeline defect identification

Compared to previous methods, this paper main approaches are:

(1) This project improves YOLOv7 for the purpose of this project. The network structure of YOLOv7 consists of input, backbone, and head. The BConv layer consists of a convolutional layer + BN layer + activation function, and the head layer integrates the features output from the backbone and predicts the features output from the previous network to obtain the class and location information of the objects in the image. This project modifies the loss function in YOLOv7 to better apply the model to pipeline defect identification and introduces the attention mechanism to satisfy the requirements of pipeline intelligent inspection for accuracy and efficiency.

(2) Moreover, this paper obtains the number of True positive (TP), True negative (TN), False positive (FP), False negative (FN) samples used in the test under different IoU thresholds, besides, calculate the average precision (AP), F1 Score, mean average precision (mAP) and Frame Per Second (FPS) for the two different networks respectively. At last, use these four metrics to evaluate performance of the model The formulas for these metrics are as follows:

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

$$recall = \frac{TP}{TP+FN} \quad (2)$$

$$F1\ score = \frac{2TP}{2TP+FP+FN} \quad (3)$$

$$AP = \sum_{i}^{n-1}(r_{i+1} - r_i)P_{interp}(r_{i+1}) \quad (4)$$

$$mAP = \frac{\sum_{i=1}^{k} AP_i}{k} \quad (5)$$

In Equation (4): $r_1, r_2, \ldots, r_n$ is the recall value corresponding to the first interpolation of the Pression interpolation segment in ascending order, $P_{interp}$ is the maximum of all Recall≥ r for a certain Recall value r under the Precision value. Equation (5), the $AP_i$ represent the value of $AP$ in different categories.

(3) Use a larger dataset containing 130,000 pictures of sewers with different defects to train model[14] and use rotation, cropping, and scaling to augment image data, additionally, At the end, using the pipelines taken in China to evaluate the accuracy and speed of

the model's intelligent recognition according to pipeline inspection standards. Moreover, this paper adopts end-to-end training method and use pre trained model to fine tuning in training models. Compared with conventional optimizer, use the latest optimizer Adan[15] which can train model faster that has been testified to enhance multiple deep learning models. Furthermore, using 10-fold cross validation to improve models' reliability.

### 3.2 Technology

The main types of techniques used in this project are shown in Table 1:

| Technology Type | Selection results |
|---|---|
| Development Tools | PyCharm, Jupyter Notebook |
| Language | Python3.8 |
| Framework | Pytorch1.13.0 |
| GUI | PyQT |
| Open-Source Library | OpenCV, CUDA11.6 |
| Environment Management | Anaconda1.7.2 |
| Operation System | Windows10 |
| Project Management | Git |
| Hardware devices | NVIDIA GeForce GTX 1660Ti GPU, i7-9750H CPU |

Table 1- Technical selections table

### 3.3 Version management plan

Version management using Git repository:
https://github.com/Lovecraftzhou/underground_pipes_finalproj.git

Version1.0: Accurate identify 16 types of defects such as pipe rupture, deformation, and deposition.
Version1.1: Enables accurate defect identification of pipeline video taken in real time.
Version1.2: Develop GUI page to view data from the inspection pipe network.

## 4 Project Management

### 4.1 Activities: tasks required to complete each objective

I.
- a) Collect and make data sets
- b) Construct neural network models
- c) Training neural network models

II.
- a) Evaluating Neural Network Models
- b) Read the relevant literature and modify the models
- c) Re-train and evaluate the model

III.
- a) Optimization model
- b) Modify model parameters

IV.
- a) Integrating the best models into pipeline intelligence recognition projects

## 4.2 Schedule

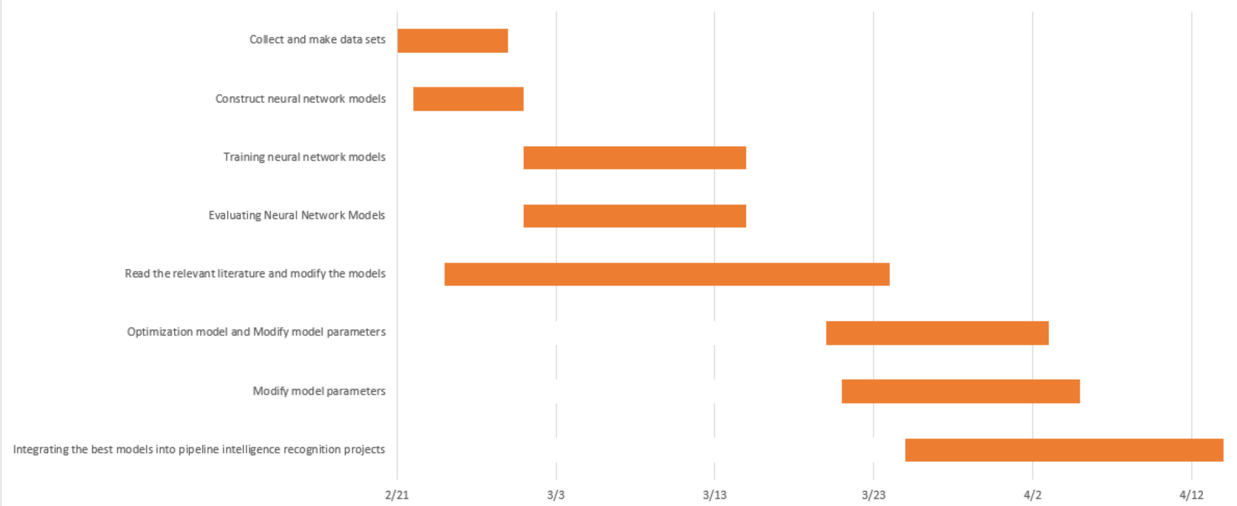


Figure 4-1 Gantt chart

## 4.3 Data management plan

Using GitHub: https://github.com/Lovecraftzhou/underground_pipes_finalproj.git

## 4.4 Deliverables

Project development document (Code)
Final Report

## 5 References


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