Imperial College London
Department of Earth Science and Engineering
MSc in Environmental Data Science and Machine Learning

Independent Research Project
Project Plan

Leveraging machine learning and remote sensing to help low-lying island nations adapt against and mitigate the effects of climate change and economic development

by
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1 Abstract

The Maldives is a small island developing state, which is particularly vulnerable to sea level rise due to its low altitude and rapid urban expansion. This project aims to leverage advanced algorithms to automatically detect coastal infrastructure, resort islands and their changes. The methodology involves image segmentation techniques to process multi-spectral and multi-temporal data from Sentinel-2 satellite and perform change detection analysis. The expected results can provide important data support for environmental impact assessment and promote sustainable development.

2 Introduction

2.1 Problem Description

Maldives is a Small Island Developing State (SIDS) of particular concern. Most of its islands are low-lying, with an average elevation of around 1 meter above sea level, making them highly vulnerable to sea level rise [1]. Along with rapid urban and marine development, large-scale construction of coastal infrastructure, resort islands, and land reclamation may seriously affect the sediment balance of these islands [2].

The goal of this project is to build a machine learning algorithm specifically for islands to automatically detect coastal infrastructure, resort islands and other construction projects from remote sensing images, automatically detect the start and end dates of construction projects. As shown in Figure 1, the algorithm must be able to accurately identify the port and coastal buildings in the image.

The results will be used in collaboration with department researchers in exploring the link between coastal construction and coastline changes. The project can provide accurate data on development activities, help the government assess environmental impacts of current projects and formulate better development strategies and policies.

Figure 1: Sentinel-2 remote sensing satellite image

2.2 Literature Review

For the identification of specific targets in remote sensing satellite images, commonly used methods include target detection and image segmentation.

Object detection is to find all objects of interest in an image and determine their categories and locations. Currently, object detection algorithms based on deep learning can be divided into two categories: two-stage detectors and single-stage detectors [3, 4]. The two-stage detector divides object detection into two stages: (1) generate proposal regions, and (2) perform classification and bounding box regression on these proposal regions [4]. Typical algorithms include Region-based Convolutional Neural Networks (R-CNN), Fast R-CNN, Faster R-CNN and Mask R-CNN. The single-stage detector predicts the bounding box and category directly from the input image without generating proposal regions. The most typical representative algorithms are You Only Look Once (YOLO), Single Shot MultiBox Detector (SSD) and Detection Transformer (DETR) [5]. Given the advantages and disadvantages of one-stage and two-stage detectors, researchers have proposed methods such as Attention Mechanism and Multi-Scale Feature Fusion. These methods improve the accuracy and speed of target detection and solve problems such as small target detection and target occlusion [6].

Image segmentation divides the image into regions with different characteristics such as colour, texture, and intensity. There are many methods for image segmentation. The traditional methods mainly include threshold-based segmentation, graph-based segmentation, edge-based segmentation, and region-based segmentation. It can segment images into different regions or objects but does not involve specific category labels or semantic information [7, 8]. In recent years, with the advancement of deep learning, a new generation of methods has emerged in the field of image segmentation. These methods can not only segment images but also assign labels to the segmented areas. State-of-the-art methods can be divided into three categories: semantic segmentation, instance segmentation, and panoptic segmentation [9]. Semantic segmentation aims to classify each pixel in an image so that each pixel is labeled as the category it belongs to. In semantic segmentation, all objects of the same category are classified into one category, but different instances are not distinguished. Commonly used algorithm models include Fully Convolutional Networks (FCNs), U-Net, DeepLab series, and Pyramid Scene Parsing Network (PSPNet. Instance segmentation not only classifies each pixel but also distinguishes different instances in the same category. Its main algorithm models include Mask R-CNN, Path Aggregation Network (PANet), TensorMask and Segmenting Objects by Locations (SOLO). Panoptic segmentation combines the characteristics of semantic segmentation and instance segmentation. It not only segments each pixel of all categories in the image but also segments and distinguishes different instances in the same category. Its main algorithm models include Panoptic FPN, UPSNet (Unified Panoptic Segmentation Network), and Panoptic-DeepLab [9].

In terms of change detection, it is the process of detecting differences by observing and identifying the state of an object at different times. To begin with, change detection methods can be divided into Pixel-Based Change Detection Algorithm and Object-Based Change Detection Algorithm [8]. Pixel-Based Change Detection Algorithm is a technique that identifies changes by comparing the spectral values of each pixel in the image. Specifically, it is mainly divided into two methods: unsupervised change detection and supervised change detection. Unsupervised change detection does not require training data and usually generates a binary change map showing the changed and unchanged areas. Common techniques used in this method include automatic threshold selection, principal component analysis (PCA), and level-set methods based on the expectation-maximization algorithm. On the other hand, supervised change detection requires training data and is implemented through post-classification comparison logic. It involves independently classifying each phase image and then extracting detailed change information by comparing the classification maps pixel by pixel. Common techniques include post-classification comparison and support vector machine (SVM) [10, 11]. In contrast, object-based change detection uses image segmentation technology to divide images into objects with the same spectral and spatial characteristics and use these objects in change detection analysis. This approach has three main steps. First, the first step is image segmentation, which is divided into independent segmentation and multi-phase segmentation. In independent segmentation, each phase image is segmented independently, which may produce sliver polygons. Meanwhile, multi-phase segmentation involves multi-phase images being segmented at the same time to generate objects that are consistent in space, spectrum, and time. Second, the step is object feature extraction. Spectral features, shape features, texture features, etc. are extracted from the segmented objects for change detection analysis. Finally, the third step is object comparison and change detection. By comparing the features of the same object at different time points, the change area is determined. Common methods include differencing, ratioing and classification [10, 11].

2.3 Objectives

Based on the description of the problem, this project can be broken down into a total of six goals to be completed. Out of these, three are identified as mandatory, while the remaining three are optional. Below is a detailed list of these six goals.

1. (Mandatory) Using the Python API of Google Earth Engine (GEE), develop Python scripts to automate the acquisition of multi-spectral, multi-temporal remote sensing imagery data from Sentinel-2 satellite.

2. (Mandatory) Leveraging Sentinel-2 multi-spectral imagery data to develop an advanced algorithm, designed to automatically detect coastal infrastructure (including jetties, and quays), construction projects such as resorts and artificial islands.

3. (Mandatory) Leveraging Sentinel-2 multi-temporal remote sensing imagery data for a specific area in the Maldives and developing a change detection algorithm based on detected targets to monitor the development and changes in the area.

4. (Optional) Train multiple image segmentation algorithm models and identify the optimal model by comparing their segmentation results.

5. (Optional) Incorporate high-resolution remote sensing data (such as imagery from Planet Labs) into the model training process to enhance the model's segmentation

accuracy for remote sensing images of varying resolutions and optimize the model's generalization ability.

6. (Optional) Collaborate with department researchers to explore potential links between coastal construction projects and coastline changes.

3 Methodology

This project focuses on identifying coastal infrastructure and coastlines such as ports and resorts and performing change detection on them. The project includes the following steps: (1) Semantic segmentation model dataset preparation (2) Image segmentation model training and testing (3) Change detection dataset preparation (4) Change detection analysis. The specific workflow of the project is shown in Figure 2.

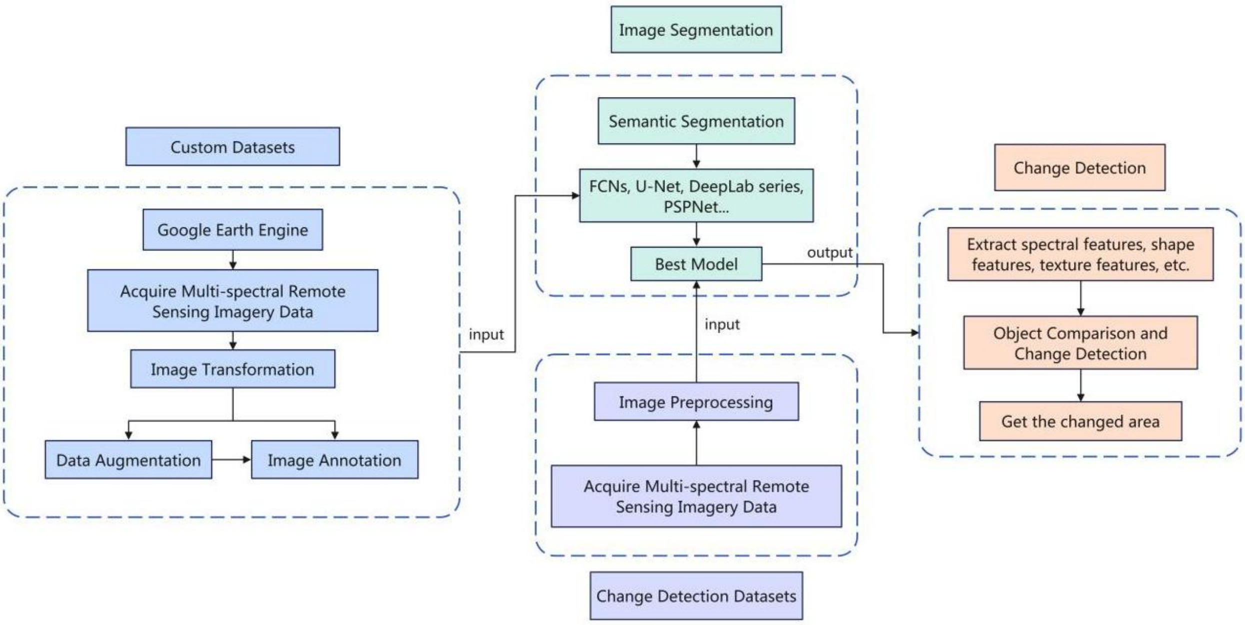

Figure 2: Flowchart of the project

4 Future Plan

- 17 Jun - 24 Jun

Learn how to use Google Earth Engine and build a dataset of annotated Sentinel-2 images.

- 25 Jun - 5 Jul

Train the image segmentation model and get a preliminary result.

- 6 Jul - 15 Jul

Try more image segmentation models and optimize the model.

- 16 Jul - 20 Jul

Acquire multi-temporal remote sensing images for change detection.

- 21 Jul - 31 Jul

Perform change detection tasks on multi-temporal remote sensing images.

- 1 Aug - 8 Aug

Optimize the change detection task and analyze the results.

- 9 Aug - 24 Aug

Complete the final report.

In order to better allocate time and manage projects, the Gantt chart shown in Figure 3 is selected as the display tool for project management.

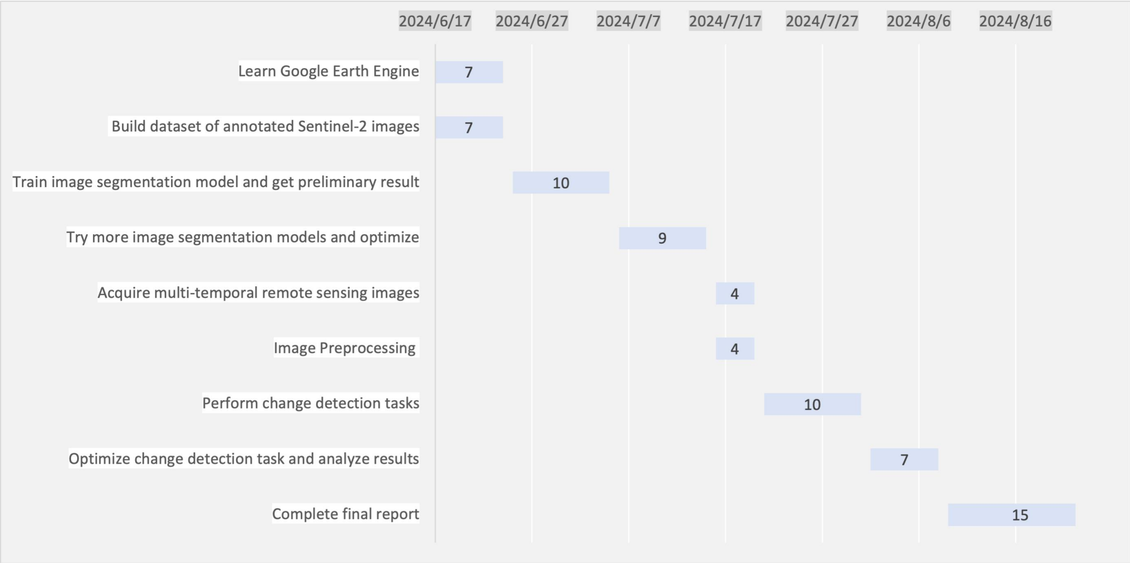

Figure 3: The gantt chart of future plan

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