Imperial College London

Department of Earth Science and Engineering

MSc in Environmental Data Science and Machine Learning

Independent Research Project
Project Plan

Cloud-based deep Learning to classify water bodies by combining the Landsat-8 and Sentinel-1 bands with different strategies

by

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1 Introduction

Locating the position of surface water is very important for agriculture and survival (Westall & Brack 2018), but it is also crucial for scientists to accurately identify surface water's location. An example where perfect accuracy for water location prediction is needed is in a property insurance company that needs to assess the probability of flooding (Balajee & Durai 2021, Kseňak et al. 2022). Standard methods to detect water include the normalized water index (NDWI) and synthetic aperture radar (SAR). However, these require a manual selection of the threshold value (Khalid et al. 2021). Depending on the location of the surface water under interest, different indices are more suitable for detection. For example, NDWI is ideal for less cloudy areas and SAR is more suitable for cloudy regions because it can penetrate the cloud (Gulácsi & Kovács 2020).

Studies were done to use machine learning methods such as Convolutional neural networks (CNN) (Gu et al. 2018) and satellite imagery to help predict water bodies more accurately. Automatic classification of the water surface is now possible due to the advancement in cloud computing and google earth engine (GEE) (Mutanga & Kumar 2019, Gorelick et al. 2017). In conjunction with machine learning, this creates opportunities to help classify the location of surface water by processing large amounts of data without needing a high-performance computer (Google 2022*b*).

Many methods to create water maps used their predictors as either the Sentinel-1 or Landsat-8/Sentinel-2 separately (Mayer et al. 2021, Li et al. 2021). A combination of data from Sentinel-1 and Landsat-8 would provide more data to the model, meaning that in a location where Landsat-8 performs worse than Sentinel-1, we could put more weights on Sentinel-1 and vice versa. Some research has combined the bands of Sentinel-1 and Sentinel-2/Landsat-8 and attempted to classify water bodies using random forests and the Generative adversarial model (GAN) (Tang et al. 2022, Jamali et al. 2021). However, these models have limitations and further investigation into combining the two bands could help improve surface water classification. To date, no research has attempted to apply multi-view learning to the water classification problem by fusing the data between Sentinel-1 and Landsat-8 (Zhao et al. 2017). This idea will be explored in this work.

In this project, the primary aim is to create a robust surface water detection tool in Thailand as Thailand is in the top 15 countries exposed to flood risk (Luo 2015). We will compare machine learning methods including random forests, CNNs and multi-view learning (Zhao et al. 2017, Gu et al. 2018) to predict the location of surface water. Afterward, the best model that generalizes across different regions will be selected. We will quantify the cost of deploying the model to the cloud and link the models to create a Google App Engine (GAE) (Google 2022*a*).

2 Literature review

Surface water is any water body above ground and around the globe, including streams, rivers, lakes and wetlands. Water has many uses such as irrigation, household uses and generating electricity (Tyson Brown 2022). Identifying the location of water is very important, not only for daily use, but also for scientists to locate areas of extreme weather such as floods and droughts (Balajee & Durai 2021). Furthermore, scientists can use water classification for further analysis such as water level prediction (Barreto et al. 2016). Hence, the ability to classify the water body accurately at any point in time and space is essential.

There are fast techniques used to detect water bodies. The bands of Landsat-8 (Acharya & Yang 2015) are used to determine the Normalized water index (NDWI), Modified normalized difference water index (MNDWI), and the Automated water extraction index for shadows (AWEI_SH) (Khalid et al. 2021). But these indices suffer from flaws in water detection especially in cloudy, snowy and areas with lots of forests. An example of where this occurs is in Nepal (Acharya et al. 2018). NDWI and Normalized vegetation index were combined to overcome the shadowing problem and detect water more accurately (Acharya et al. 2018). In addition, another satellite Sentinel-1 or SAR at C-band (Attema et al. 2009) was discovered to outperform Landsat-8's NDWI because SAR can penetrate the atmosphere and detect water regardless of the cloudiness (Kseňak et al. 2022). However, selecting the threshold for SAR or NDWI is manual and certain combinations of indices are more optimal for different locations.

The detection of surface water has become automated and more accurate through supervised classification with machine learning methods. Machine learning models have removed the need to manually select a threshold. However, one of the challenges in this topic is that supervised machine learning requires labelled data, which is often challenging to find and at a low resolution to match the satellite's resolution. The most common data used as the labelling data is the JRC Monthly Water History (30m) (Mayer et al. 2021, Tang et al. 2022, JRC/Google 2022) and the OpenStreetMap (OSM). An example of a study has been able to use CNN with Landsat-8 bands to classify water bodies with OSM (Li et al. 2021) in Germany. Other studies have seen the benefits of using SAR imagery and deep learning for automatic water detection using the U-net network model with JRC Monthly data (Mayer et al. 2021) in Cambodia. The U-net model was applied to classify land cover because of its ability to capture spatial information with limited data (Alom et al. 2018, Ulmas & Liiv 2020).

Since, Landsat-8 and sentinel-1 were launched in February 2013 and April 2014, respectively (Acharya & Yang 2015, Attema et al. 2009) the dates overlap. Hence, it is possible to combine the features of the two satellites. Some attempts to combine the bands for Landsat-8 with Sentinel-1 to detect water bodies in China use random forests (Tang et al. 2022). An unsupervised learning technique using GANs was used to train networks without labelled data to classify water (Jamali et al. 2021). Another emerging deep learning method called multi-view learning is perfect for fusing data. An example of where multi-view learning was used is audio + video, text + text at different time stamps (Li et al. 2018, Zhao et al. 2017). Currently, no research has applied multi-view learning to water classification problems.

Cloud computing and GEE have made it possible to train the machine learning models without consuming laptop computer memory (Mayer et al. 2021). In addition, it is possible to deploy models in the cloud and link them to Google Javascript code editors to create a GAE. GAE enables a web application to be created so anyone can look at your trained models without understanding the code like classifying landcover in dynamic world (Brown et al. 2022). There is a cost tied to hosting neural network models to GAE, but machine learning methods in the earth engine module such as random forest and support vector machine are free to use. The four main financial costs include hosting the neural network model, training the model, using the stored model to predict and storing the data in storage buckets (Google 2022*a*).

3 Problem Description and Objectives

The objective is to build the most robust and accurate model to classify water bodies. Classifying water bodies is important for basic government monitoring and for insurance companies to perform flood risk assessments accurately. We will build Random Forest, CNN and a multi-view neural network for the water classification problems using the Sentinel-1 and Landsat-8 bands. The best model will be selected and discussed. The model will be initially trained in Thailand. If there is enough time, the training region could be extended to other countries to make the model more robust.

This problem is broken down into five main milestones.

Milestones:

1. Image processing so that all images have the same time frame and selecting the regions of

interest

2. Trained Machine learning techniques with Random Forest, CNN and multi-view neural network
3. Hyperparameter tuning for all the machine learning methods and searching for the best neural network architecture
4. Validating the results against hand labelled data and temporal changes in water
5. Either Deploying the model into the GAE for anyone's accessibility or create an easily reproducible code in Google Colaboratory (GC) that links to Google Cloud Platform (GCP).

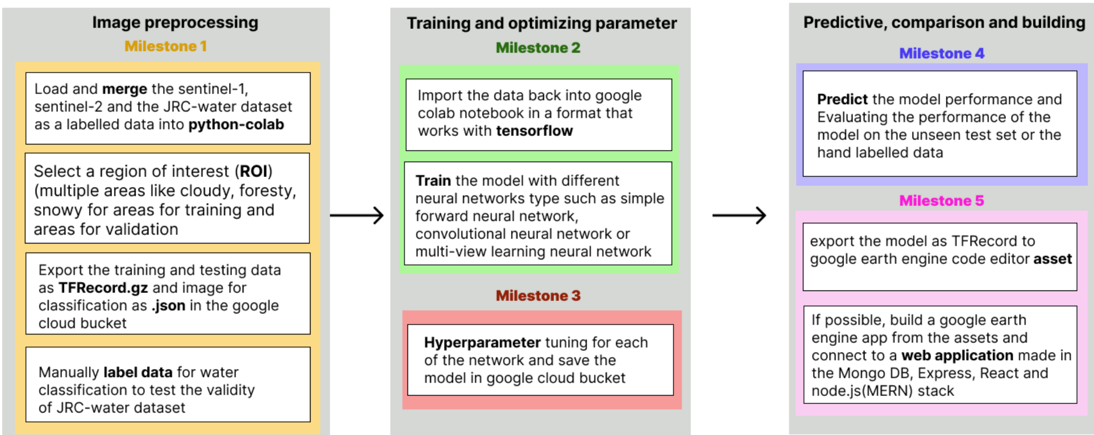

Figure 1: Plan for the project separated as image preprocessing, training/hyperparameter tuning, predicting and deploying GEE apps.

4 Progress to Date and Future Plans

Current tasks completed: The milestones are touched upon but we still need to go into more depth

- Understanding and successfully training a fully connected network model in GC and utilizing the GCP in a single area of interest. (milestone 1)
- Looked at Gini importance in the random forest to help understand multi-view (Wei et al. 2020). (milestone 1)
- Explored basic Multi-view neural network implementation on a single area of interest (milestones 1 and 2)
- Trained basic Random forest and Support vector machine. (milestone 2)
- The Preliminary metrics for F1 score and accuracy were coded (milestone 4)
- Finished Deploying a website that connects to GAE and can be found at https://geeimperial.herokuapp.com/ (milestone 5)

The proposed preliminary multi-view network in figure 2 is applied to classify water using a single area of interest as shown in figure 3. The labelled dataset being used is the JRC global water monthly dataset (Pekel et al. 2016, JRC/Google 2022). Here we sampled only a rectangular point of interest in a lake in Thailand and predicted the water bodies in Nepal with five different methods. We can see that the results are not perfect and more room exists to investigate by extending to training in multiple locations. For example, the number of samples could be increased to multiple rectangles. For plans and current progress please refer to the Gantt chart in figure 5.

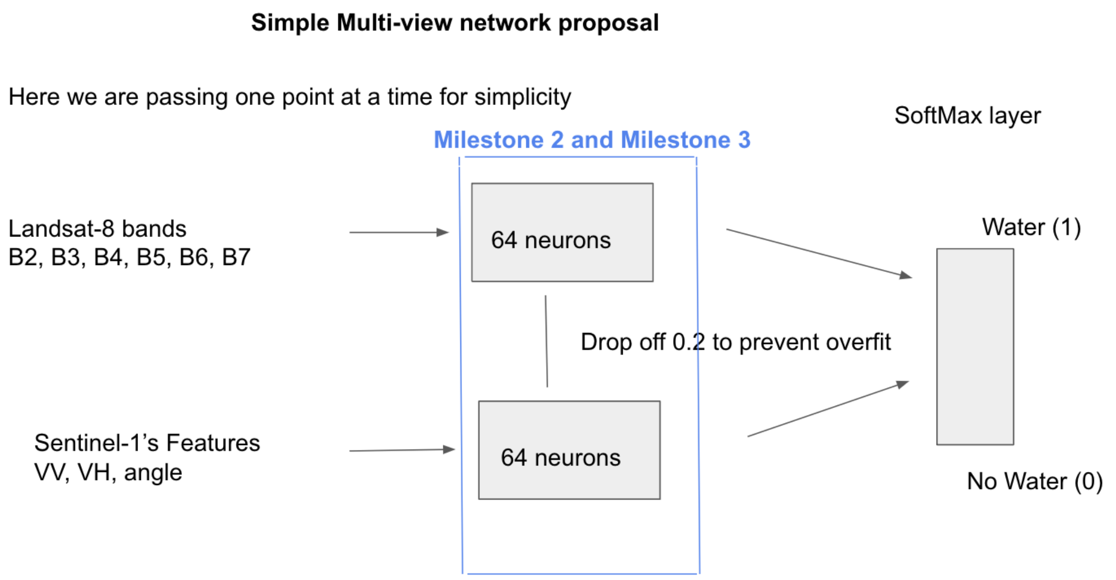

Figure 2: Preliminary multi-view network that is coded up and can be improved and we can modify the inner structure of the neural network with CNN to capture more spatial information.

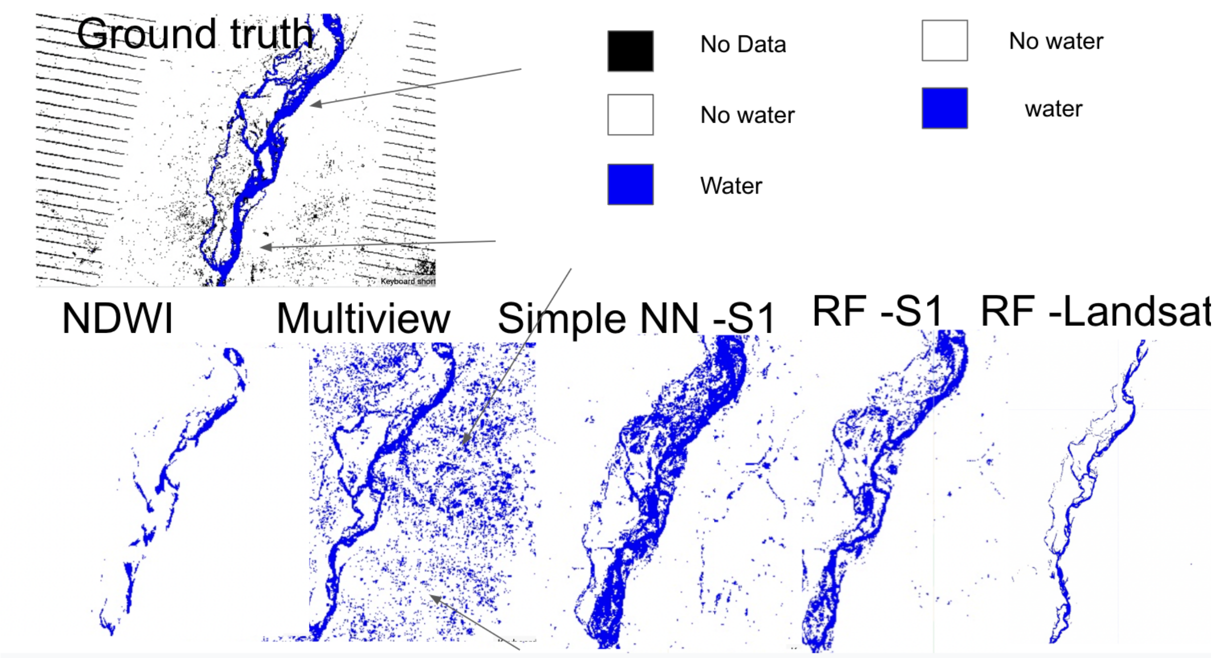

Figure 3: The figure above has six images. The first image indicates the ground truth of the water location of an area of interest in Nepal. The figures below illustrate five different techniques to classify water using satellite imagery. (1) NDWI was used, (2) Multi-view learning for a simple neural network architecture was implemented, (3) Simple neural network architecture with Sentinel-1 data was used, (4) Random forest with Sentinel-1 data, (5) Random forest with Landsat-8 dataset.

	Train Acc	Val Acc	Test(unseen) Acc	F1-Score	Precision	Recall
RF-S1	0.992	0.984	0.877	0.132	0.725	0.0730
RF-landsat	0.999	0.994	0.994	0.723	0.938	0.588
SimpleNN-S1	0.987	0.987	0.755	0.0875	0.0460	0.902
Simple Multiview	0.999	0.999	0.995	0.870	0.909	0.833

Figure 4: The table shows the result for the performances of different machine learning methods including the accuracy, F1-score, precision and recall metric

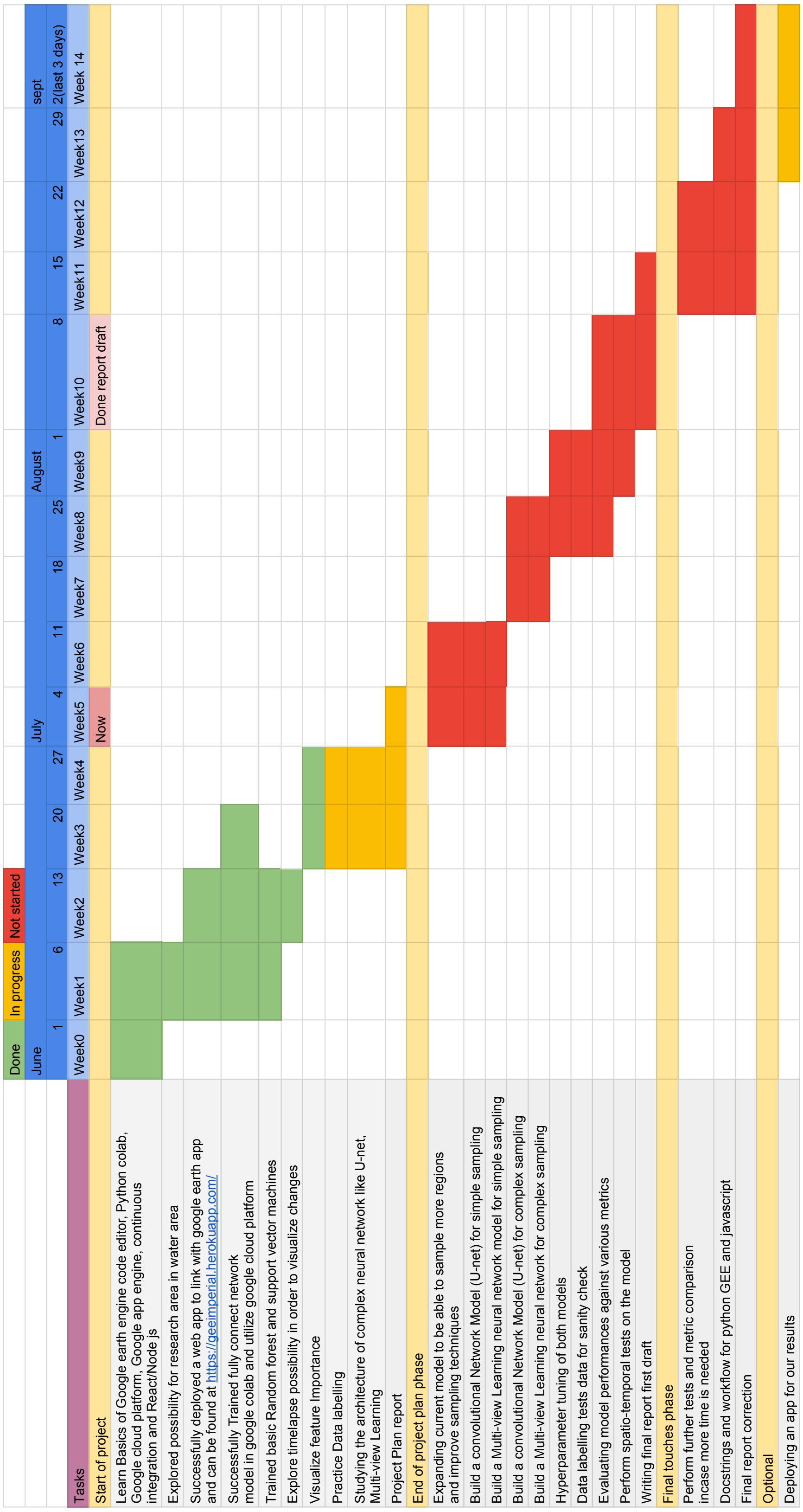

Figure 5: The gantt chart below illustrates the progress and future date plan. **Risk**: it may be not possible to obtain a hand labelled data using labelling tools such as label box (Labelbox 2022), but even so we have other labelling data to try to validate against.

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