Dr. Vishwanath Karad
MIT WORLD PEACE UNIVERSITY | PUNE
TECHNOLOGY, RESEARCH, SOCIAL INNOVATION & PARTNERSHIPS

School of Computer Engineering & Technology

Extraction of River Networks from Satellite Images

Mid-Term Review

Sukrut Bidwai 1032191717
Devang Jagdale 1032180072
Tejas Hiremath 1032180097
Neil Bhutada 1032181209

Group No: B58

Project Guide:
Dr. Sukhada Bhingarkar

Introduction

1. Extraction of water bodies from satellite imagery has been broadly studied for many reasons, eg: mapping of natural resources, drinking water supplies, food production, agricultural planning, and disaster management, etc.
2. With the growth of global warming, it became essential to maintain the sustainable management of these resources for the preservation of human life.
3. Few methods attempted to allocate water bodies from different satellite imagery in both spatial and spectral domains.

Motivation

Extraction of River network will definitely help in agricultural activities such as keeping a track record of Rivers over time period. Which would inversely also help in detection of river drying. River network extraction could possibly help in any sort of network extraction from provided images. Planning of ecosystem can be done without disturbing the river network to avoid further damages.

Objectives

1) To pre-process image dataset, with respect to uniform defined size.
2) To implement different classification techniques with automatic feature extraction for mapping of rivers network from high resolution multispectral satellite image.
3) To Evaluate different classification techniques by a comparative study with the performance measures.
4) To estimate the width of the river at regular intervals along the longitudinal traverse.

Literature Survey

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Sr No.	Name of Author	Paper name	Methodology	Gap	Publication Details
01.	Carey Ciaburri, Monica Kiehnle-Benitez, Alaa Sheta and Malik Braik	Automatic extraction of rivers from satellite images using image processing techniques	Enhancement of images using the decorrelation, image segmentation, clutter removal	It could not generalize the set of parameters that can be used for all image segmentation and background removal.	May-2020, Accents Journal
02.	Wei, Z.; Jia, K.; Liu, P.; Jia, X.; Xie, Y.; Jiang, Z.	Large-Scale River Mapping Using Contrastive Learning and Multi-Source Satellite Imagery	Contrastive learning process to extract representative hidden features from multi-spectral data and SAR da	2 datasets used, 1. Extremely Low-res images. 2. Noisy dataset.	July-2021, MDPI

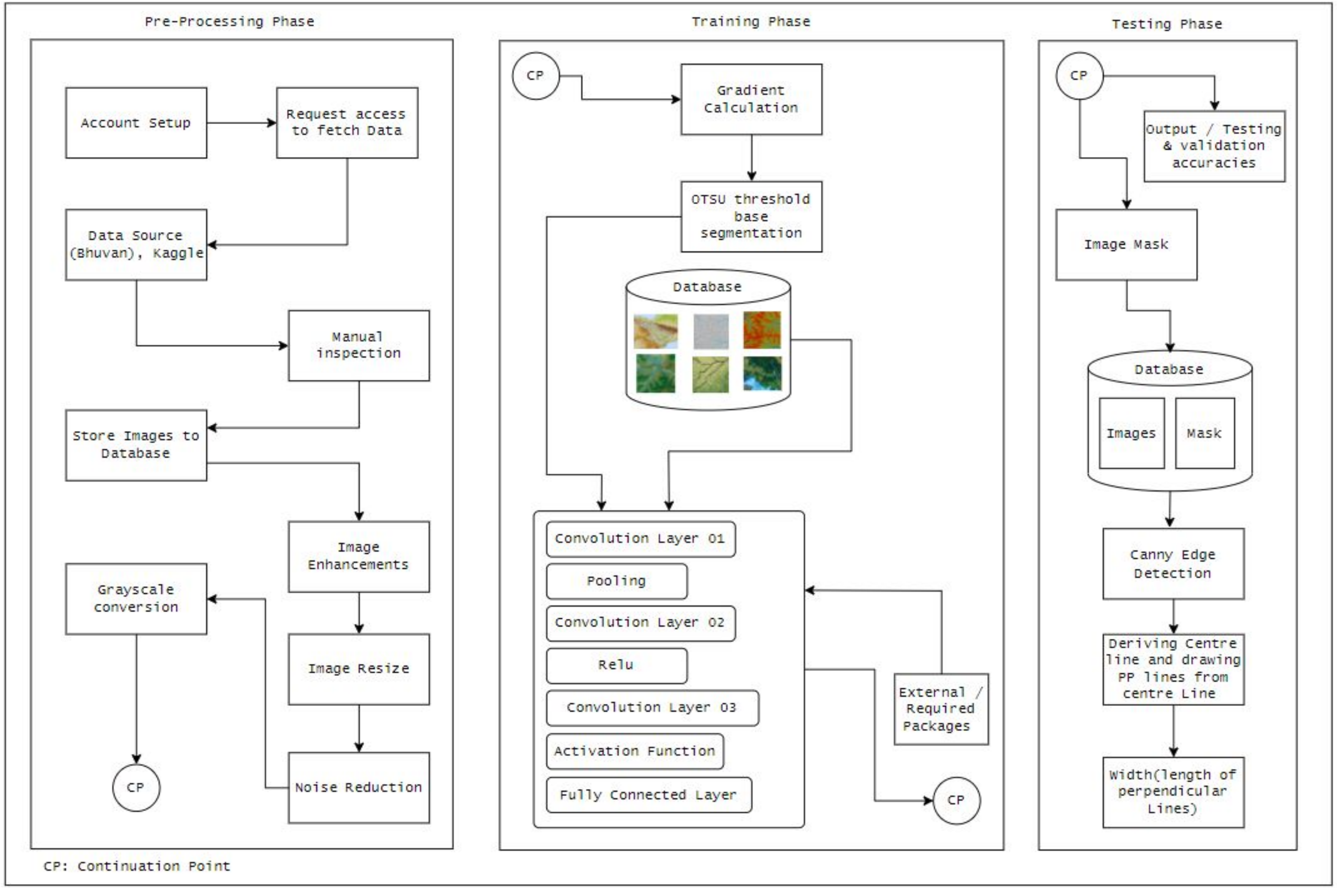
Sr No.	Name of Author	Paper name	Methodology	Gap	Publication Details
03.	Xiao Yang , Tamlin M. Pavelsky , George H. Allen , and Gennadii Donchyts	An Automated Google Earth Engine Algorithm for River Width Extraction From Remotely Sensed Imagery	calculating width at certain intervals and measuring the river width along the centre line.	It does not factor in errors in in situ width measurements or mismatches between in situ and satellite measurement locations in areas where width changes rapidly	Feb 2020, IEEE
04.	Anju Asokan, J Anitha	Machine Learning based Image Processing Techniques for Satellite Image Analysis -A Survey	Enhancement, Segmentation, Classification	unwanted artifacts and background information in the satellite images.	Feb 2019, IEEE

05.	Yudie Wang, Zhiwei Li , Chao Zeng , Gui-Song Xia and Huanfeng Shen	An Urban Water Extraction Method Combining Deep Learning and Google Earth Engine	The framework is divided into two main parts: 1) offline training with MSCNN, and 2) online prediction on GEE.	Image dataset was only of 36 images	Feb 2020, IEEE
06.	Zeba Naaz , Dr.G.Malini Devi	River Network Classification from Multi-Spatial Satellite Imagery using Random Forest	**Feature extraction using Gabor filter and canny edge detectors, training and testing the random forest model**	Final images contains lot of noise.	Sept 2021 IJERT
07.	Mengya Li, Penghai Wu, Biao Wang, Honglyun Park, Hui Yang, Yanlan Wu	A Deep Learning Method of Water Body Extraction From High Resolution Remote Sensing Images With Multi Sensors	**A new network is proposed, called the dense-local-feature-compression (DLFC) network aiming at extracting water body from different remote sensing images automatic**	Small water bodies below the image resolution exist in the form of mixed pixels. Mapping of water bodies with less than 2 pixels were not drawn.	2021 IEEE

08.	Guojie Wang, Mengjuan Wu, Xikun Wei, Huihui Song	Water Identification from High-Resolution Remote Sensing Images Based on Multidimensional Densely Connected Convolutional Neural Networks	DenseNet model is proposed, based on the multidimensional densely connected CNN for identifying water in the Poyang Lake area.	Optimal threshold to extract water varies with region and time	March 2020, MDPI
09.	François Waldner, Foivos I. Diakogiannisb	Deep learning on edge: Extracting field boundaries from satellite images with a convolutional neural network	The ResUNet was used as backbone in the architecture, along with different post processing methods like watershed methods.	Dataset was collected in a small duration	Feb 2020, Elsevier

10.	Deepika Rani ,Viswanath Kapinaiah	Extraction of River from satellite image	Identification and removal of noise using suitable filters and using k-means and region growing segmentation techniques for river extraction.	Climatic conditions and shadows were not taken into consideration.	May 2017, IEEE

System Architecture



Result

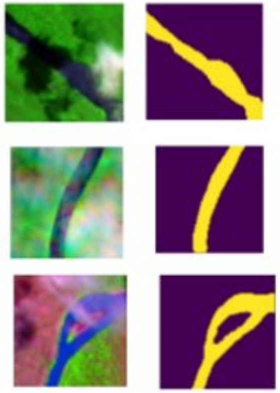
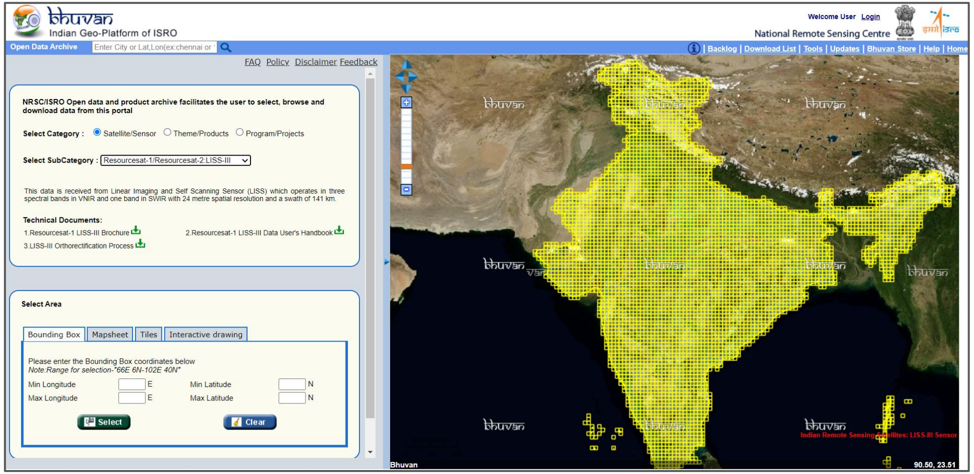
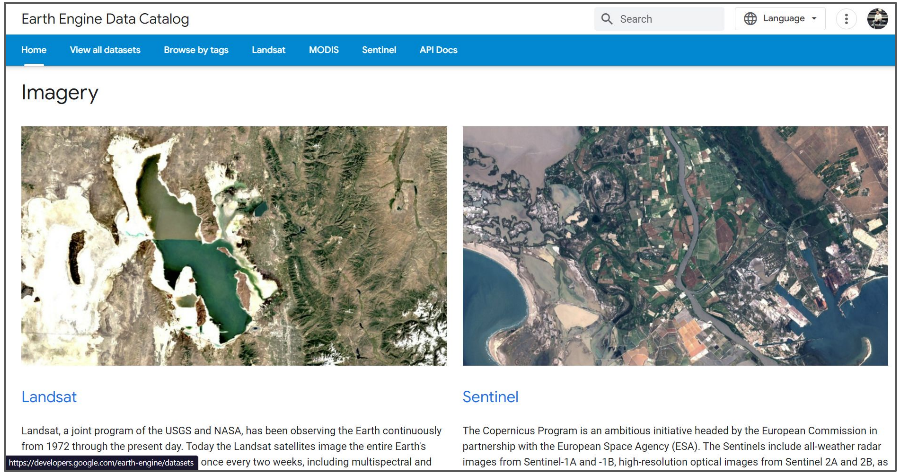


Image Dataset Collection



Bhuvan.nrsc ISRO Satellite Image Data source

Google Earth Engine Satellite Image Data Source



Dataset Details

Open Data Archive | Enter City or Lat,Lon(ex:chennai or '

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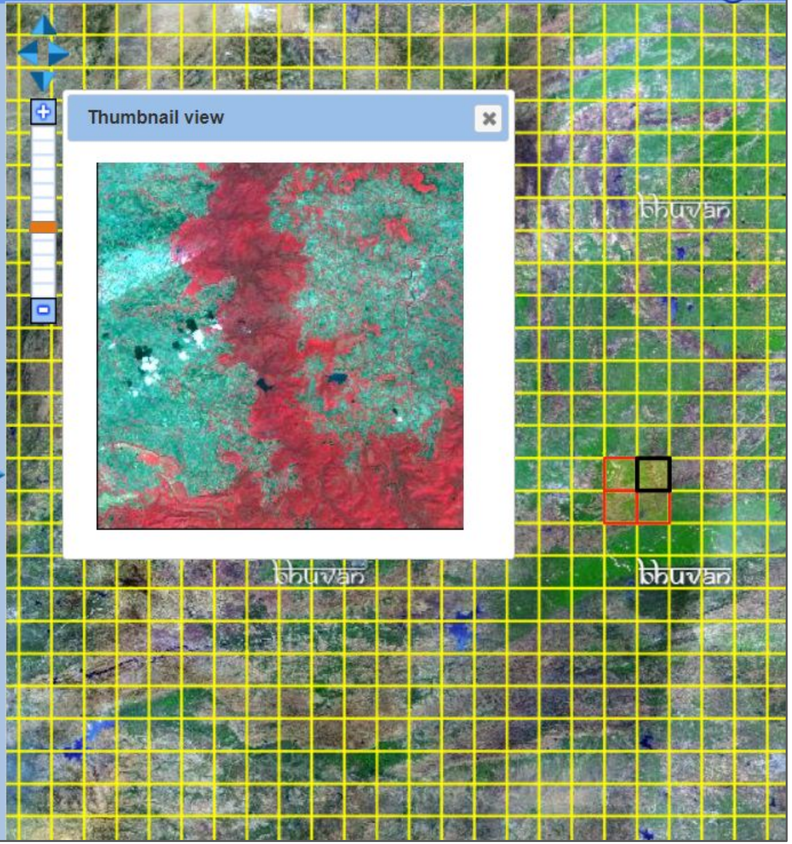


Methodology / Algorithms Used

Methodology Consists of 2 steps:

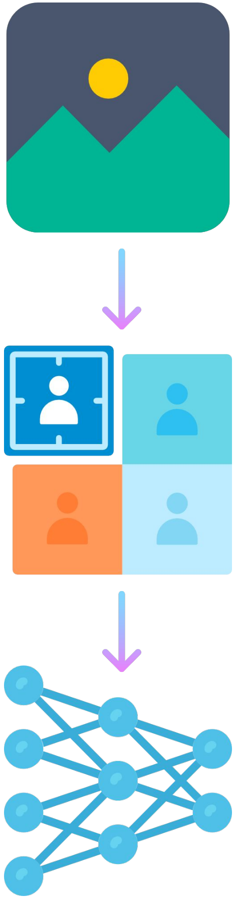
1. Image Pre-processing
2. Use of Machine Learning Predefined Algorithms / User Defined Algorithms for Training, Testing and Validating the Dataset

Image Pre-processing implemented using 2 sub methods:

1. Image Segmentation
2. OTSU

Machine Learning Algorithms Used for Training, Testing & Validations:

1. UNet
2. KNN (K-Nearest Neighbour)
3. SVM (Support Vector Machine)
4. LGB (Light Gradient Boosting)



Hardware / Software Requirements

Hardware Requirement:

intel Core i5 VRAM 2GB RAM 8GB

Software Requirements:

Windows 10 / 11

Python Version 3.10.0

Jupyter Notebook

Google Colab (Web Version)

1. **Dataset:** A collection of water bodies images captured by the Sentinel-2 Satellite. Contains 2841 images https://www.kaggle.com/franciscoescobar/satellite-images-of-water-bodies
2. **Image Dataset Collection Sources:**
   https://search.earthdata.nasa.gov/search?m=17.0859375!64.265625!4!1!0!0%2C2
   https://bhuvan-app3.nrsc.gov.in/data/download/index.php

Outline

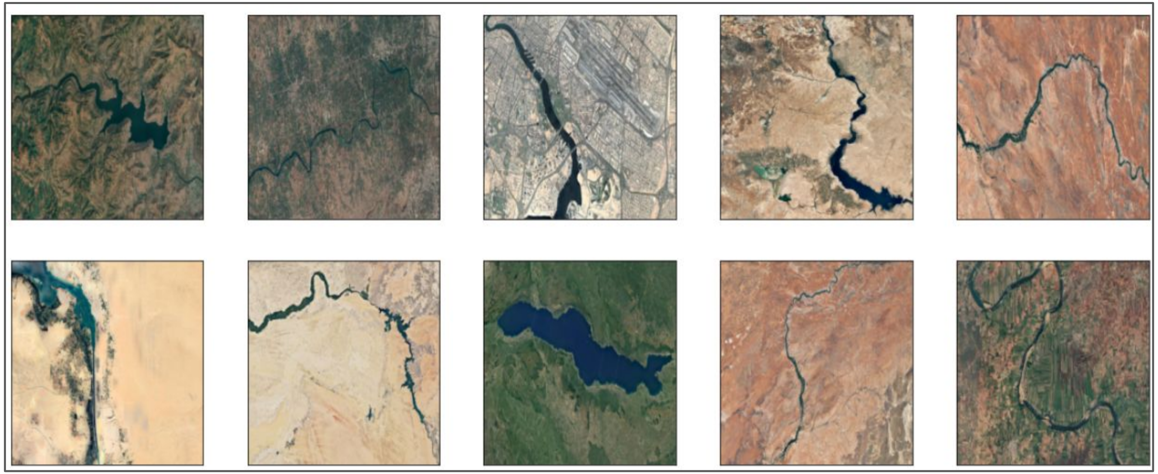
- Introduction
- Motivation
- Objectives
- Literature Survey
- System Architecture
- Methodology / Algorithms Used
- Basic Implementation Details
- Conclusion

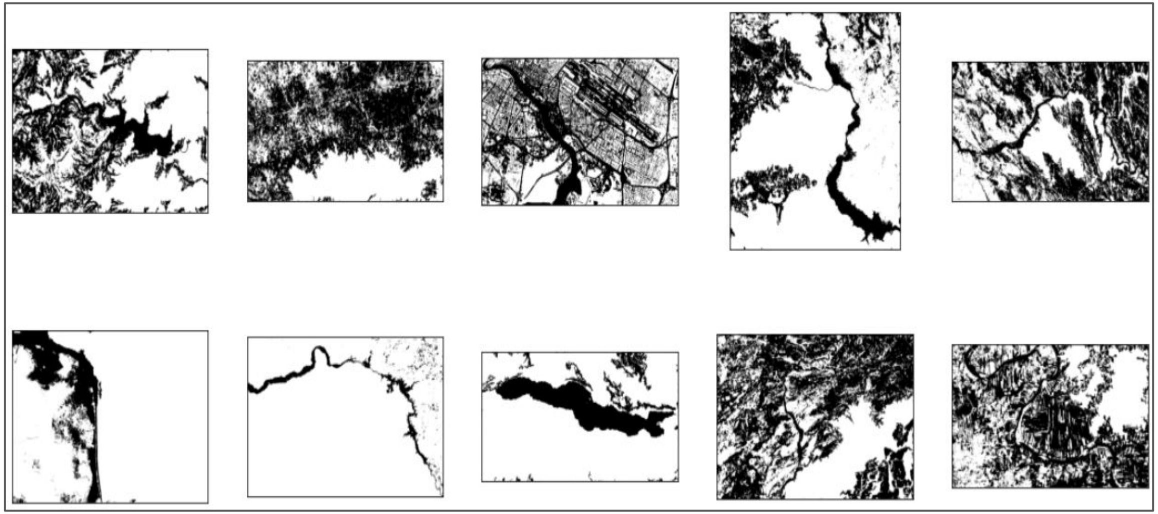
Basic Implementation Details

1. Collection of Image Dataset from Satellite Images using Bhuvan.nrsc / Google Earth Engine
2. Dataset Filtering
3. Applying Image Processing Un-Supervised Machine Learning Algorithms such as:
   a. OTSU
   b. Global Thresholding
   c. K-means
4. Applying Machine Learning Algorithms as follows:
   a. UNet
   b. KNN (K-Nearest Neighbour)
   c. SVM (Support Vector Machine)
   d. LGB (Light Gradient Boosting)
5. Predictions and Validations Carried out.

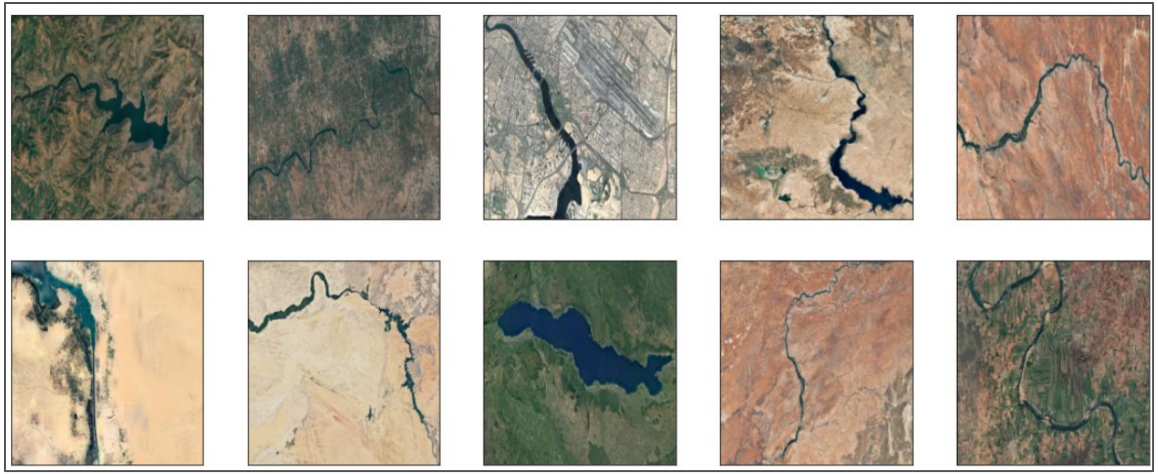
IMAGE PROCESSING

OTSU Method



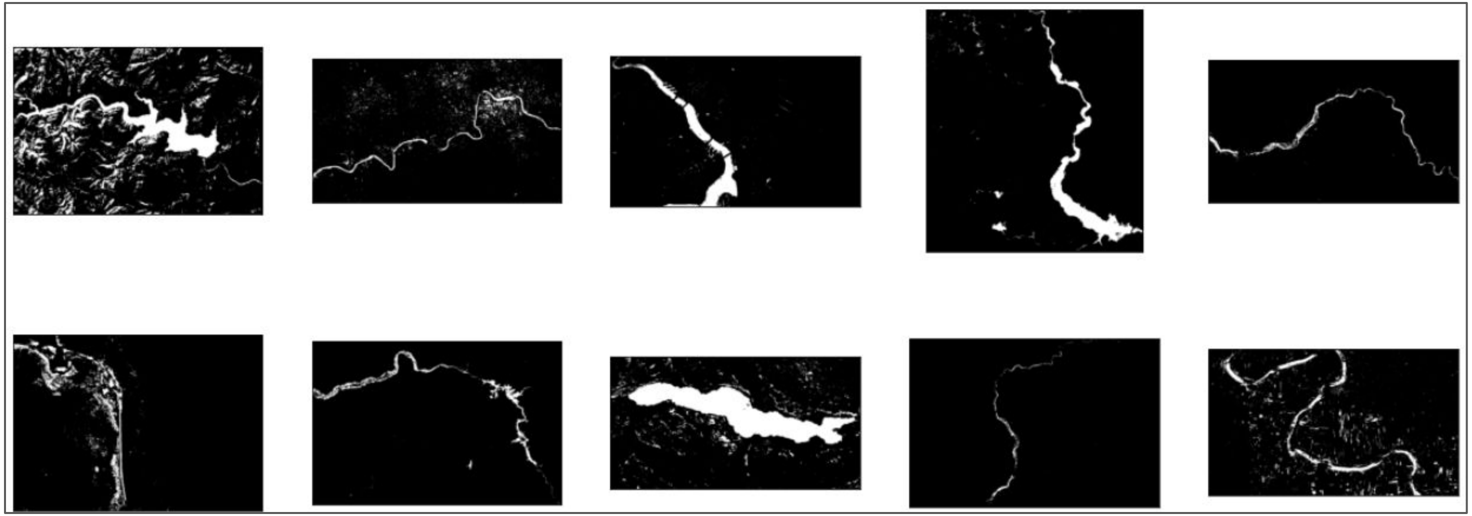


Otsu's method is a global image thresholding algorithm. Otsu's Thresholding Concept Automatic global thresholding algorithms usually have following steps. Process the input image Obtain image histogram (distribution of pixels) Compute the threshold value



Global Thresholding

The simplest of all thresholding techniques is to partition the image histogram by using a single global threshold, T. Segmentation is then accomplished by scanning the image pixel by pixel and labeling each pixel as object or background, depending on whether the gray level of that pixel is greater or less than the value of T. As indicated earlier, the success of this method depends entirely on how well the histogram can be partitioned.



Machine Learning

U-Net Model Summary

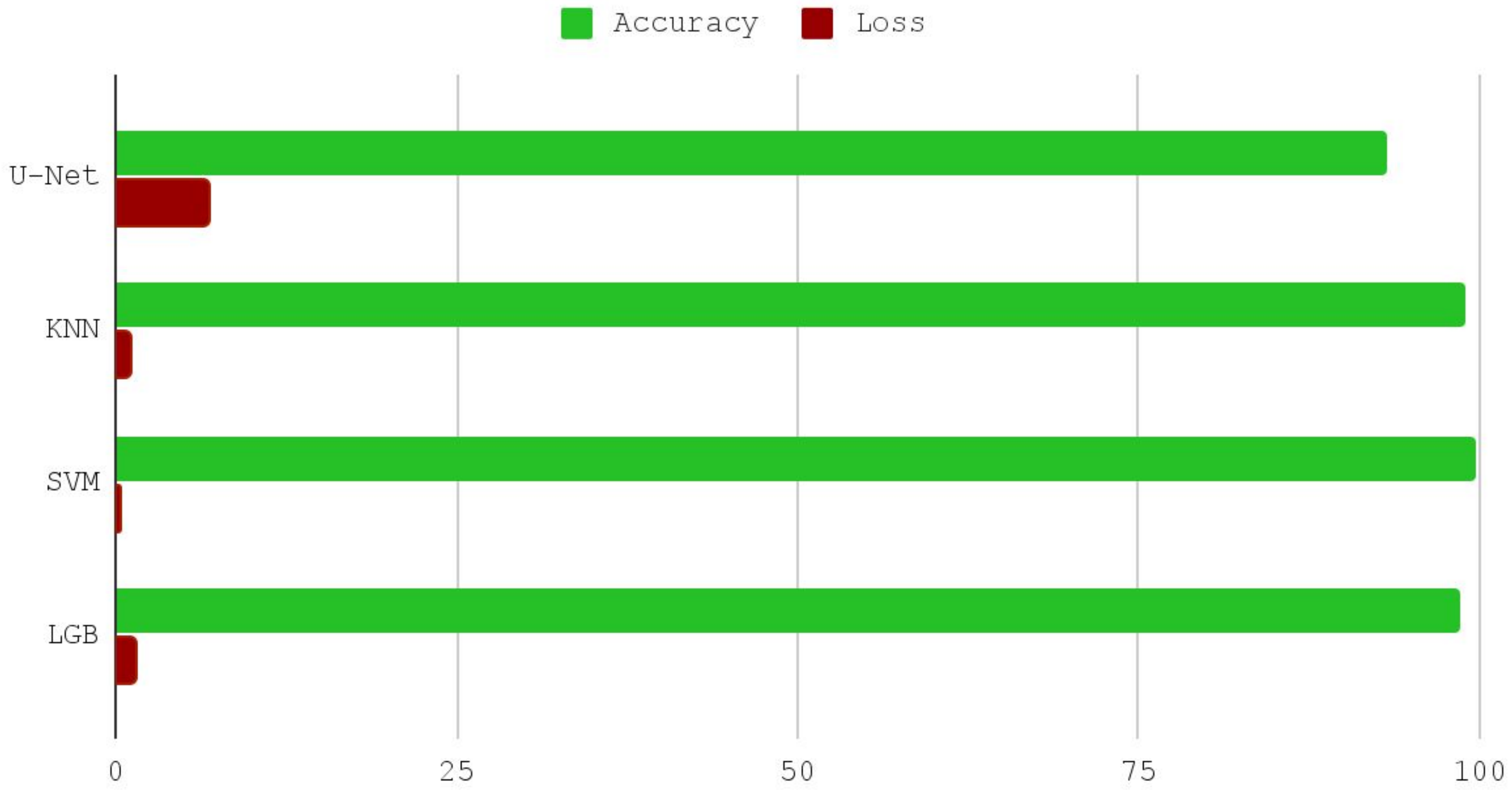
The UNET architecture contains two paths. First path is the contraction path (also called as the encoder) which is used to capture the context in the image. The encoder is just a traditional stack of convolutional and max pooling layers. The second path is the symmetric expanding path (also called as the decoder) which is used to enable precise localization using transposed convolutions. Thus it is an end-to-end fully convolutional network (FCN), i.e. it only contains Convolutional layers and does not contain any Dense layer because of which it can accept image of any size.

```
Conv2d 53 Layers
Up-Sampling 2d 8 layers
3 Max Pooling Layers
Total params: 1,925,601
Trainable params: 1,925,601
Non-trainable params: 0
```

Difference between KNN Algorithm Summary and SVM Algorithm Summary

Support Vector Machines (SVM) and k-Nearest Neighbor (kNN) are two common machine learning algorithms. Used for classifying images, the kNN and SVM each have strengths and weaknesses. When classifying an image, the SVM creates a hyperplane, dividing the input space between classes and classifying based upon which side of the hyperplane an unclassified object lands when placed in the input space. The kNN uses a system of voting to determine which class an unclassified object belongs to, considering the class of the nearest neighbors in the decision space. The SVM is extremely fast, classifying 12 megapixel aerial images in roughly ten seconds as opposed to the kNN which takes anywhere from forty to fifty seconds to classify the same image. When classifying, the kNN will generally classify accurately; however, it generates several small misclassifications that interfere with final classified image that is outputted. In comparison, the SVM will occasionally misclassify a large object that rarely interferes with the final classified image. While both algorithms yield positive results regarding the accuracy in which they classify the images, the SVM provides significantly better classification accuracy and classification speed than the kNN.

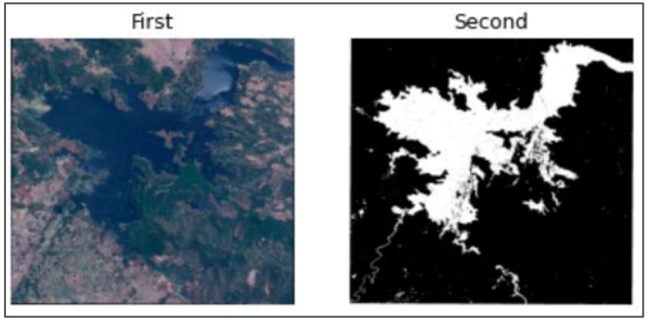
Machine Learning Models Accuracy vs Loss

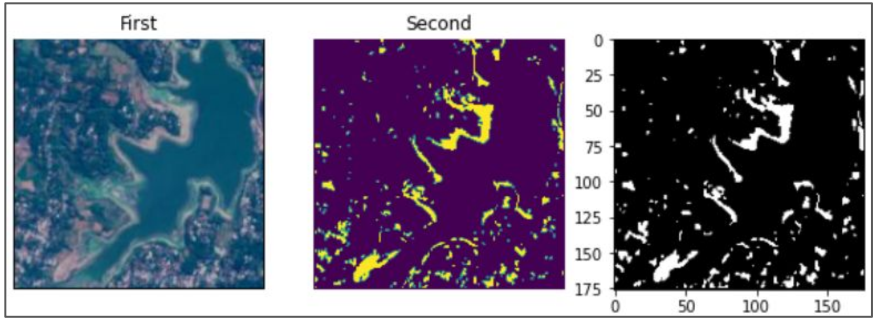


93.3	6.7
98.9	1.1
99.8	0.2
98.6	1.4

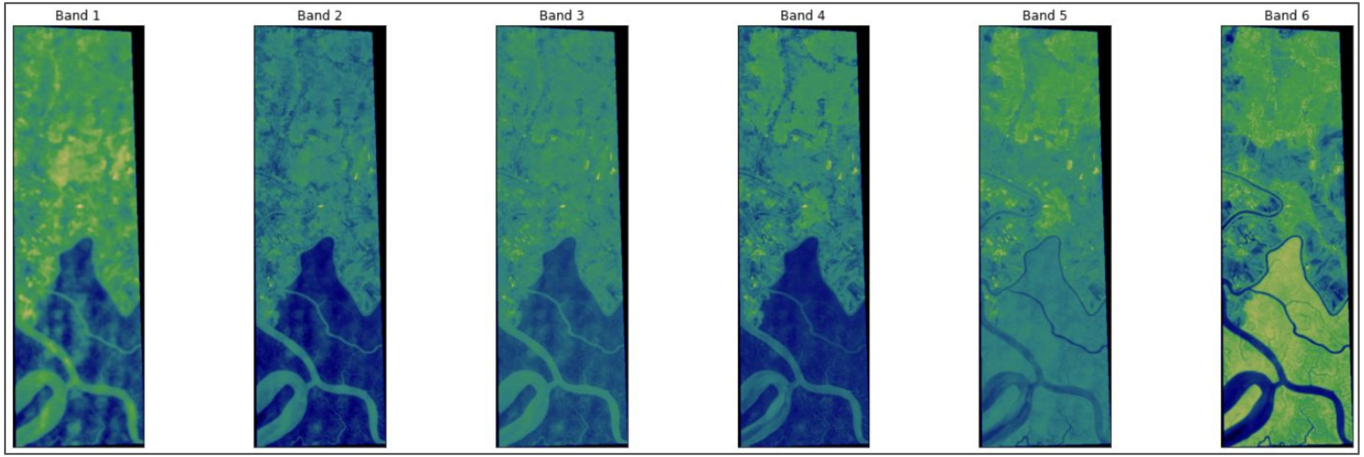
Machine Learning Implementation Output

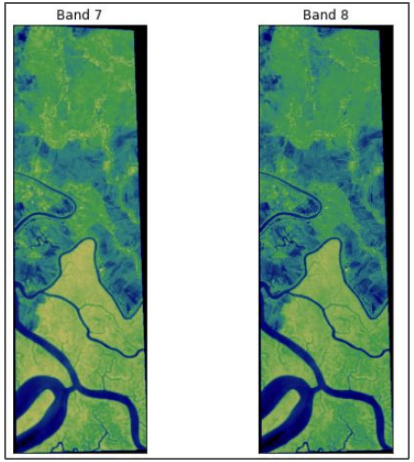
U-Net





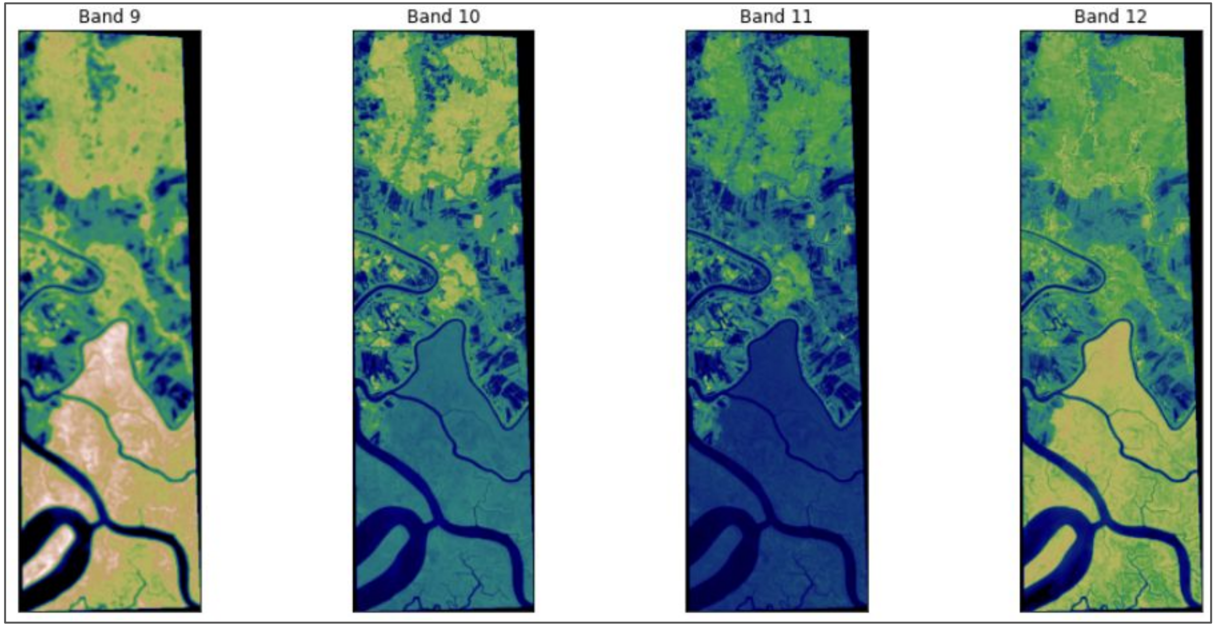
KNN





Machine Learning Implementation Output

KNN



Future Prospect / Implementation

1. SegNet Implementation
2. Mask R CNN Implementation
3. Use JPG images for KNN Algorithm

Conclusion

Image processing and Machine learning models give an accurate predicted river masks for satellite images. But this method is applicable for only one type of image. If the images contain a wide spectrum of filters like clouds, shadows, snows, etc. It does not adapt and applies an iterative method for all. If we have all images of the same kind then image processing might be an appropriate choice. If we use predefined CNN models, we might get masks with lower accuracy as it is generalized and not specifically developed for river network extraction. We can develop combined predefined CNN models or tweak some of its parameters to get higher accuracy. In this way we have used U-net, KNN, SVM, LGB methods for extraction of River networks to keep track of water resources through satellite imagery with acceptable accuracies within models.

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Thank You