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Motivation / Importance

Detecting water bodies from satellite images using object based techniques is crucial for various applications. It aids environmental monitoring by tracking aquatic ecosystems and supporting conservation: water resource management benefits from precise mapping of rivers and lakes, while disaster management relies on accurate water body detection for flood ~~detection~~ prediction and response. Urban planning and infrastructure development use this data to make informed decisions, minimizing environmental impact. Agriculture benefits from real-time water resource date for irrigation planning, and climate change monitoring relies on tracking water body changes over time. This automated approach is cost-effective and efficient, allow for quick analysis of large geographical areas.

Problem Statement

Traditional methods for detecting water bodies are slow and prone to errors, hindering environmental monitoring, disaster response and urban planning. Automated object-based detection in satellite images offer a faster, efficient, simpler alternative, but it faces challenges in accuracy, varied geographic contexts, and distinguishing water from similar features.

A reliable object based approach for water body dectection is needed. It must be adaptable to different environments, accurate in diverse conditions, and processing large scale data efficiently. Addressing these issues is essential.

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Literature Survey:
Automatic detection of water bodies from satellite imagery has been an active area of research, given the importance of mapping and monitoring surface water resources. Traditional pixel-based methods have been superseded by more advanced object-based techniques that leverage the power of deep learning and multi-scale analysis.

One notable paper is "You Only Look Twice: Rapid Multi-Scale Object Detection in Satellite Imagery" by Guo et al. [1], which proposed a multi-scale CNN architecture called "YOLT" for rapid object detection in satellite imagery, demonstrating its effectiveness in identifying water bodies. In another work by the same authors, "The Effects of Super-Resolution on Object Detection Performance in Satellite Imagery" [2], they investigated the effects of super resolution techniques on object detection performance, highlighting the potential benefits of enhancing image resolution for improved water body delineation

The paper, "Geospatial Object Detection in High Resolution Satellite Images Based on Multi-Scale Convolutional Neural Network" by Guo et al. [3] developed a multi-scale CNN model tailored for geospatial object detection, including water bodies, in high-resolution satellite imagery, leveraging features at multiple spatial scales

In a comprehensive review titled "State-of-the-Art Deep Learning Methods for Objects Detection in Remote Sensing Satellite Images" by Adegun et al. [4], the authors summarized the state-of-the-art deep learning methods for object detection in remote sensing satellite images, with a particular focus on water body detection, highligting the strengths and limitations of various architectures.

The study "Object detection in high resolution optical image based on deep learning technique" by Qi [5] explored the use of deep learning techniques for object detection in high-resolution optical satellite images, demonstrating their efficacy in detecting water bodies among other objects of interest.

"Sentinel-1" SAR Images and Deep Learning for Water Body Mapping" by Pech-May and Aquino-Santos [6] investigated the use of Sentinel-1 synthetic aperture radar (SAR) data and deep learning models for water body mapping, showcasing the potential of radar data in this domain

"Satellite Detection of Surface Water Extent: A Review of Methodology" by Li et al. [7] provided a comprehensive review encompassing both traditional and advanced techniques, including deep learning approaches, for satellite-based detection of surface water extent.

One study titled "Deep Learning detection of types of water-bodies using optical variables and ensembling" [8] explored the use of optical variables and ensemble methods for deep learning-based detection of different types of water bodies.

The paper "Deep-Learning-Based Multispectral Satellite Image Segmentation for Water Body Detection" by Yuan et. al. [9] proposed a deep learning-based approach for segmenting multispectral satellite images to detect water bodies, leveraging the rich spectral information available in such datasets.

Finally "Water-Body Area Extraction from High Resolution Satellite Images - An Introduction, Review and Comparison" by Nath and Deb [10] presented as introduction review, and comparison of various techniques for extracting water body areas from high-resolution satellite images, providing a comprehensive overview of the field.

Overall, the literature highlights the rapids advancements in automatic water body detection from satellite imagery, driven by the integration of deep learning, multi-scale analysis, and other cutting-edge techniques, demonstrating their potential to improve accuracy and efficiency in water resource mapping and monitoring

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Model Architectures

YOLT - You Only Look Twice

Single Pass detection, easy to scale with high quality images. Very common model for computer vision and image analysis.

Architecture

Layer	Type	Filters	Size/Stride	Output Size
0	Convolutional	32	3x3/1	416 x 416 x 32
1	Maxpool		2x2/2	208 x 208 x 32
2	Convolutional	64	3x3/1	208 x 208 x 64
3	Maxpool		2x2/2	104 x 104 x 64
4	Convolutional	128	3x3/1	104 x 104 x 128
5	Convolutional	64	1x1/1	104 x 104 x 64
6	Convolutional	128	3x3/1	104 x 104 x 128
7	Maxpool		2x2/2	52 x 52 x 64
8	Convolutional	256	3x3/1	52 x 52 x 256
9	Convolutional	128	1x1/1	52 x 52 x 128
10	Convolutional	256	3x3/1	52 x 52 x 256
11	Maxpool		2x2/2	52 x 52 x 256
12	Convolutional	512	3x3/1	26 x 26 x 512
13	Convolutional	256	1x1/1	26 x 26 x 256
14	Convolutional	512	3x3/1	26 x 26 x 512
15	Convolutional	256	1x1/1	26 x 26 x 256
16	Convolutional	512	3x3/1	26 x 26 x 512
17	Convolutional	1024	3x3/1	26 x 26 x 1024
18	Convolutional	1024	3x3/1	26 x 26 x 1024
19	Passthrough		10 → 20	26 x 26 x 1024
20	Convolutional	1024	3x3/1	26 x 26 x 1024
21	Convolutional	N_f	1x1/1	26 x 26 x N_f

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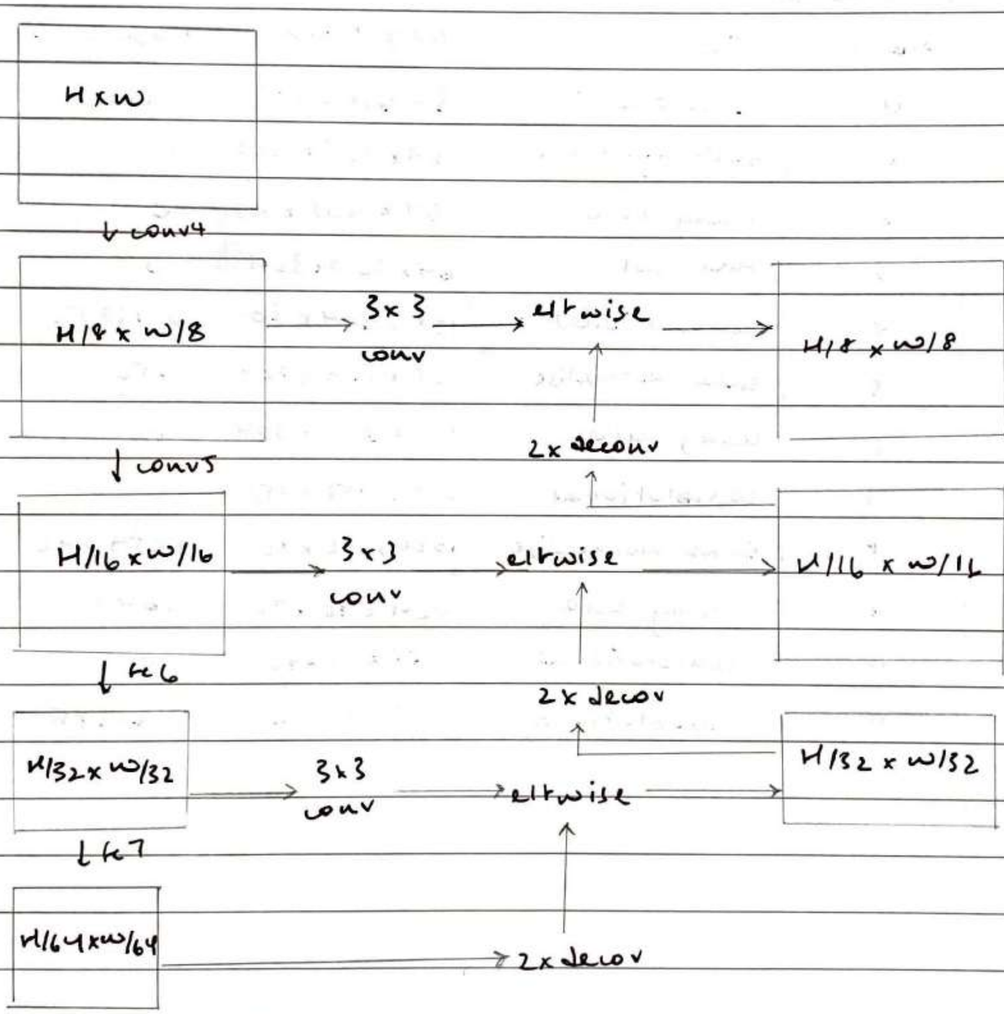
Multi scale Base Network

Made to process input at varying scales to pick up macro and micro details

Architecture



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YOLOv8 - You Only Look Once

Support for image detection, segmentation and pose estimation. Excels in real time performance like video analysis, automatic diving and surveillance

Architecture

Number	Type	Output Size	Parameters
0	Convolutional	3 x 608 x 608	1792
1	Batch Normalise	64 x 608 x 608	128
2	Leaky ReLU	64 x 608 x 608	0
3	Max Pool	64 x 304 x 304	0
4	Convolutional	128 x 304 x 304	73856
5	Batch Normalise	128 x 304 x 304	256
6	Leaky ReLU	128 x 304 x 304	0
7	Convolutional	128 x 152 x 152	0
8	Batch Normalise	1024 x 76 x 76	2359296
9	Leaky ReLU	1024 x 76 x 76	2048
10	Convolutional	255 x 76 x 76	0
11	Convolutional	255 x 76 x 76	261375

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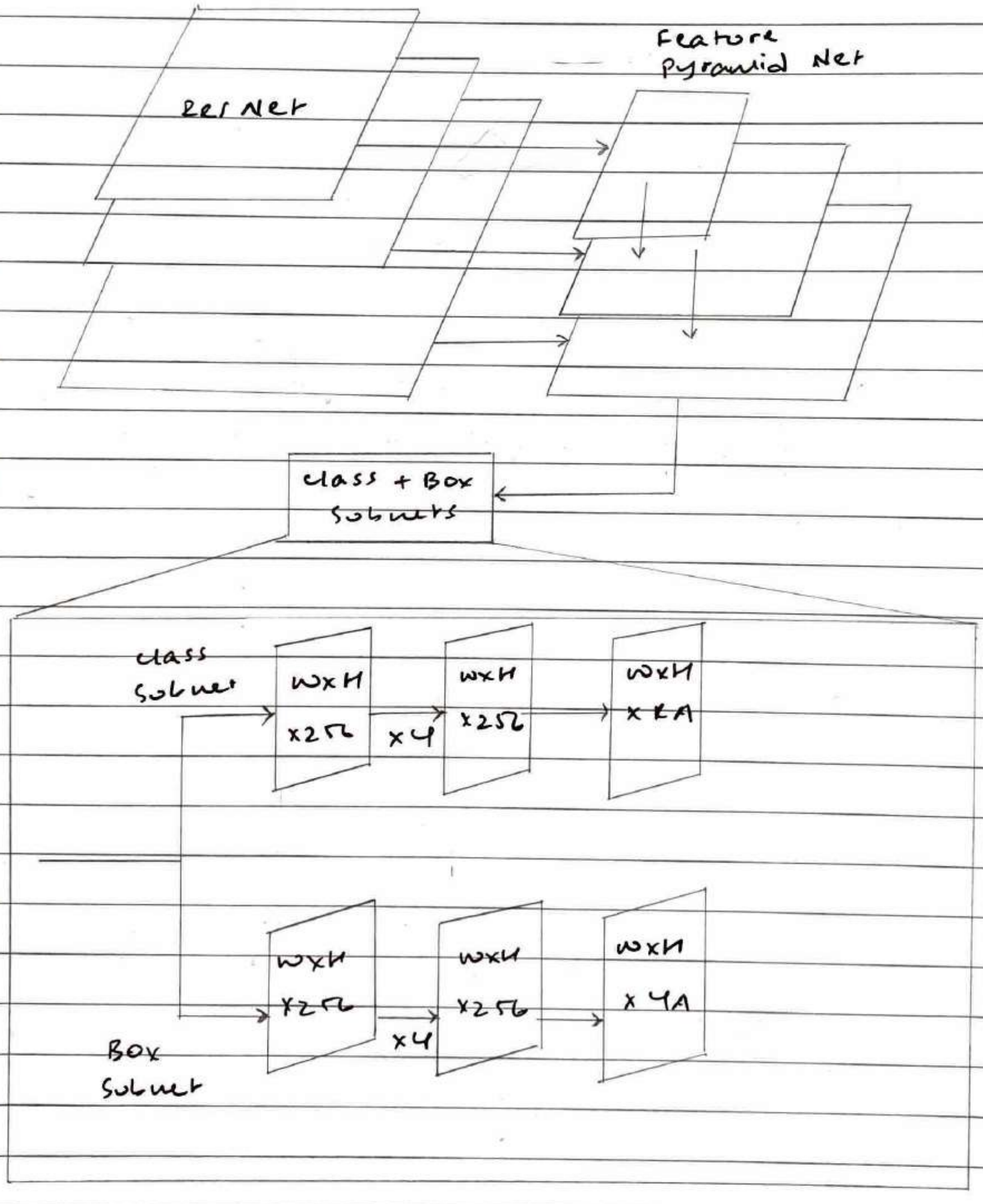
RetinaNet

Model to detect objects with high accuracy and with great robustness. Features include a focal loss function and a two stage architecture

Architecture



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Performance Metrics

U-net results:

Epochs	Metric	Percentage
25	precision	82%
	Recall	40%
	F1	53%
50	Precision	81%
	Recall	78%
	F1	79%
75	Precision	74%
	Recall	72%
	F1	73%
100	Precision	94%
	Recall	92%
	F1	93%

Model comparison over Nam co water extraction

Model	Accuracy	Kappa
NDWI	0.9951	0.9898
CART	0.9937	0.9869
SVM	0.9963	0.9924
Object Oriented	0.9464	0.9905
Deep learning	0.9878	0.9746

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Model comparison over AquaSat

Model	Accuracy	Precision	Recall	F1
Decision Tree	1	1	1	1
Cat Boost	0.98	0.98	0.98	0.98
XG Boost	0.91	0.91	0.91	0.91
Random Forest	0.91	0.90	0.91	0.90
Logistic Regression	0.9	0.9	0.9	0.9
SVM	0.9	0.9	0.9	0.9

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Summary of results obtained in the articles referred :

Recent years have seen impressive advancements in object detection and water body mapping from Satellite imagery, driven by deep learning techniques and high-resolution remote sensing data. Researchers have tackled challenges like object scale variations and image complexity

In the paper, "You Only Look Twice : Rapid Multi-Scale Object Detection In Satellite Imagery" by Etoo et al., they proposed a fully convolutional neural network pipeline (YOLT) to rapidly localize vehicles, buildings, and airports in satellite imagery. It achieved object detection F1 scores of around 0.6 - 0.9 depending on the category. It demonstrated the ability to train on one sensor and apply the model to a different sensor.

"The Effects of Super-Resolution on Object Detection Performance in Satellite Imagery" by Shermeyer and Van Etten found that super-resolution techniques as a pre-processing step can improve object detection performance at most resolutions. The greatest benefit was achieved at the highest resolutions, with super-resolving 30cm imagery to 15cm yielding a 13-36% improvement in mean average precision (mAP)

The paper on the multi-scale CNN for object detection in high-resolution satellite imagery demonstrated the effectiveness of the proposed method on the NWPU

VHR-10 dataset and showed its superiority over state-of-the-art approaches.

In the study on object detection using the tripleSAT dataset, the RetinaNet model achieved high mAP of over 90% for detecting wind turbines, airplanes, and oil storage tanks in high-resolution optical imagery.

The paper reviewing state-of-the-art deep learning methods identified limitations in detecting objects due to factors like high inter-class similarity and intra-class diversity in remote sensing images. YOLOv8 achieved promising performance of 68% precision and 60% recall on their proposed dataset.

The study using Sentinel-1 SAR data and deep learning found that rigorous training with many samples and iterations was crucial for high precision water body mapping, achieving 94% precision, 92% recall, and 93% F1 score with 1036 samples and 100 epochs.

The review paper on satellite detection of surface water extent discussed challenges like the trade-off between spatial and temporal resolution, mixed pixels, lack of universality in methods, and the need for standardized evaluation metrics. It highlighted the potential of multi-source data fusion and cloud computing platforms.

"Deep learning detection of types of water bodies using optical variables and ensembling" utilized the AquaSat dataset and proposed a stacked ensemble model consisting of multiple neural networks and a machine learning classifier. The stacked ensemble model with a decision tree classifier achieved 100% accuracy on the imbalanced test data.

"Deep-learning-Based Multispectral Satellite Image Segmentation for Water Body Detection" by Yuan et al. proposed a novel deep convolution neural network (DCNN) approach called MC-WBDN for water body extraction from multispectral satellite imagery. Experimental results showed MC-WBDN outperformed traditional water indices and other deep models on RGB and multispectral data in detecting water bodies.

The paper by Nath and Deb provided a review and comparison of various techniques for extracting water body areas from high resolution satellite images. The paper reviews methods such as SAR imagery analysis, techniques based on NDWI, NDVI indices, decision tree and programming methods, thresholding and clustering approaches, supervised and unsupervised classification algorithms, edge detection, data fusion.

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Identification of open problems and directions:

One major problem is handling the trade-off between spatial and temporal resolution when working with satellite imagery for water body detection. Future work should explore fusing multi-source, multi-resolution data to leverage the complementary advantages of different sensors. Another challenge lies in mixed pixels, where water bodies appear mixed with other surface types, requiring advanced techniques for accurate extraction. Developing super-resolution mapping and mixed pixel decomposition approaches is crucial.

Establishing standardized evaluation metrics and benchmarks is an important future direction to facilitate objective comparison and ranking of diff water body extraction techniques. Moreover, the emergence of cloud computing platforms presents an opportunity to develop scalable global-scale water body mapping solutions that can enable large-scale, long-term monitoring of surface water dynamics across the globe

From a methodological standpoint, while deep learning has shown promise, there is further scope for enhancing model architectures, training strategies, and data augmentation technique specifically tailored for water body detection in satellite imagery. Addressing challenges such as high inter-class similarity, intra-class diversity, and complex backgrounds could lead to performance improvements. Additionaly, investigating multi-modal data fusion by combining optical and SAR data could potentially overcome limitations of individual sensor types.

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