# Lake Detection via Pre-trained Deep Models: Optimization and Comparative Insights

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This research focuses on the classification and segmentation of water bodies using multispectral satellite images. It uses deep learning models, such as convolutional classifiers and semantic segmentation networks. Pretrained models are employed as a foundation due to their ability to capture rich, transferable features from large-scale datasets, thereby improving generalisation. Four primary datasets were employed in this work: EuroSAT RGB dataset, a Kaggle satellite imagery collection with corresponding water body masks [1], the Sentinel-2 Earth Surface Water Dataset, and a Sentinel-2 dataset from Google Earth Engine filtered by water occurrence. These datasets differ in data format, spatial resolution, and spectral characteristics, encompassing both RGB or multispectral imagery.

**Additional Keywords and Phrases:** multispectral satellite imagery, ResNet, U-Net, NAU-Net

## 1 Introduction

The accurate delineation of water bodies is inherently challenging due to spectral confusion with features like snow [3] and the difficulty in establishing robust global thresholds owing to atmospheric and inter-image variability [2, 4, 5]. This research seeks to address these limitations by optimizing pre-trained deep learning models for improved inland water detection via targeted fine-tuning on a diverse, aggregated dataset and provide comparative insights.

## 2 Models and Methodologies for Lake Detection

The classification models (ResNet18 and ResNet34) were developed to distinguish between lake and non-lake imagery. The fine-tuning process included unfreezing layers, incorporating dropout and ReLU into the final layers, and using label smoothing for improved generalisation. Models were trained using a combination of multispectral images (from which B4, B3 and B2 bands were extracted) and standard RGB images.

U-Net and NAU-Net were used to segment the data. NAU-Net was more sensitive to water than U-Net, although it still showed low accuracy (16% F1-score and roughly 10% mean IoU). NAU-Net's utilisation of multispectral input still offered it an advantage over the trained model [6].

## 3 Results

### 3.1 Classification Models

ResNet18 and ResNet34 outperformed the baseline models pretrained on ImageNet, achieving over 97% (Table 1) in both validation accuracy and balanced accuracy. Despite their strong performance, the models occasionally misidentified ambiguous landscapes, such as rivers or snow-covered places, particularly in cloudy images. These misclassifications emphasises the variability issue in satellite images [2]

Table 1: Performance Metrics for ResNet Classification Models

| **Metric** | **ResNet18 (Val)** | **ResNet34 (Val)** |
|---|---|---|
| Training Accuracy | 98.54% | 97.58% |
| Validation Accuracy | 97.66% | 97.28% |
| Validation Loss | 0.2361 | 0.2515 |

## 3.2 Segmentation Models

U-Net, trained show slightly modest result compared with the pre-trained NAU-Net, which has a better accuracy. One persistent issue relates to the Otsu threshold's sensitivity, which **limited the reliability of automated binarization processes** (Figure 1).

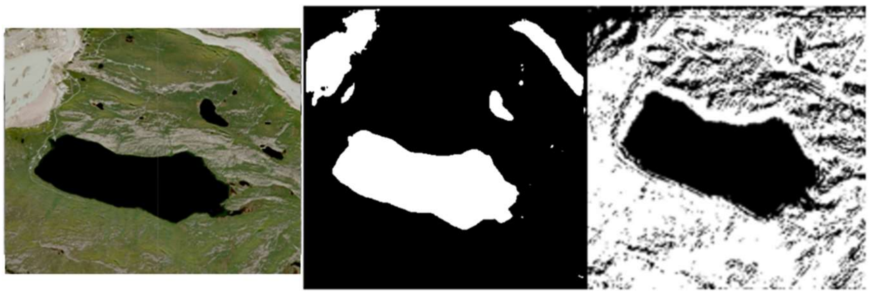

**Figure 1:** On the left the original image, the right NAU-Net result, in the middle U-Net result

# 4 Conclusion

Integrating robust classification models, such as ResNet, with specialized segmentation networks like U-Net, is highlighted in this work as being effective for the task of water body detection. Although some challenges remain, especially in precisely distinguishing unclear boundaries between land and water, the proposed approach demonstrates strong potential for practical use in remote sensing and large-scale monitoring of water bodies.

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