International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Water Bodies Segmentation Through Satellite Images Using ResNet

G. Silpalatha* **and Dr. T. S. jayadeva**

Submitted:13/03/2024 **Revised**: 28/04/2024 **Accepted**: 05/05/2024

Abstract: Images by the satellites are useful for analysing and managing water bodies. Precise segmentation of water bodies by the images from the satellites can be used for various purposes, including flood management, environmental monitoring, balancing ecosystem and for civilization. Although the existing UNets data efficiency is quite limited because of its huge amount of annotated data for training, which is costly and time dwelling. Computational requirements and memory usage can be increased by its symmetric architecture. It may struggle with global context, producing boundary artifacts. It also faces challenges with class imbalance, which can lead to biased predictions. It also consumes a lot of time for training. So for this purpose an innovative and effective method of water body segmentation is essential that is ResNet50, a DCNN design well known for its effectiveness in image recognition tasks. This is the approach utilizes hierarchical features learned by ResNet50 to precisely identify water bodies, from the images by satellites, among complex backgrounds. By combining preprocessing techniques, data augmentation, and fine-tuning of the ResNet50 model, the semantic segmentation performance can be increased. This work presents a proposed solution for satellite image monitoring of the water body. To accomplish this objective, we have introduced the ResNet model, this is a semantic segmentation model of an image. This method has successfully got through a validation accuracy of 96.02 % for water segmentation with an error of 20.22%. Additionally, we conduct comparative analyses with existing techniques to demonstrate the lead of proposed approach. This paper presents a promising solution for automating water bodies segmentation in satellite imagery, thereby enabling us to efficiently monitor and management of water resources on a large scale.

Keywords: *Satellite imagery, ResNet, Semantic segmentation, Water body.*

1. Introduction

There has been a significant improvement of technology in recent years, with deep learning being a major component in automating task works such as object detection, classification and segmentation of an image. Deep learning work with Convolutional neural networks (CNN) play an crucial role in image segmentation, especially in satellite imagery, where satellite images provide an overview of monitoring temporal changes, fishing, landscapes and weather forecasting. DL inspired by the structure and functioning of human brain. It has neural networks, which are computational models which consists of layers of interconnected nodes. These networks perform simple mathematical operations and have weights adjusted during the learning process, thus decreases the error between the actual and predicted out put. To decrease the difference between predictions and actual labels, deep learning models learn from huge amounts of labelled data using algorithms. The of process training includs supply of input data, comparing it with the desired output, adjusting weights using optimization algorithms like gradient descent and calculating errors. Convolutional Neural Networks (CNNs) are useful for image recognition, transformer models for natural language processing (NLP) and Recurrent Neural Networks (RNNs) for sequential data. Deep learning can be used in various areas, like computer vision, healthcare, natural language processing, speech recognition, finance and autonomous vehicles. Challenges involved are large amounts of data, interpret ability, computational resources and over-fitting. Recent advancements include improvements in model architectures, optimization algorithms and techniques for handling challenges like data scarcity and domain adaptation. In the field of satellite imagery UNet is a CNN network that is designed segmentation of an image [1] and [2]. Based on these features through up-sampling, it is operated by extracting features through down-sampling and generating segmented masks. This supervised nature requires training data, but the network learns to identify features within the masks by analysing images alongside their corresponding masks.

In satellite images, water segmentation [3] is very important for remote sensing, for analyzing images, and various processes like flood management, urban planning and weather forecast. CNNs (Convolutional Neural Networks) work had demonstrated promise in data segmentation with semantic tasks, improving accuracy and robustness. This method can be useful in fields such as agriculture, weather forecast, hydrology and urban planning, enabling better understanding and management of water bodies and ecosystems.

ResNet, which is a deep neural network, aacknowledge the issue of disappearing gradients by learning residual mapping, the difference between input and required output. In this process enable to skip any number of layers, this process of skipping layers is known as skip

School of Electronics, Reva University, Bengaluru- 560064, Karnataka, India.
**Corresponding author: gsilpalatha.ece@gmail.com*

connections. Which bypasses one or more layers, making it possible to the gradient to flow more directly during back-propagation.There are several residual blocks in ResNet's architecture, each containing numerous convolutional layers and skip connections, creating a very deep network with hundreds or even thousands of layers. ResNet50, a deep learning model [4], is being used for accurate water body segmentation by the images by satellites. This is crucial for ecological studies, eco-system monitoring, weather forecast, resource management and urban planning. It can learn complex or difficult features from the images by satellites, transfer learning for specific tasks and scale efficiently. ResNet50 can be very beneficial, particularly to know the flood prone areas, flood management and decreasing the damage due to floods. It is also useful in urban planning, by locating the suitable place for building up of projects in this way environmental impacts can be minimized on them. The model's high accuracy in image recognition tasks makes it a reliable choice for accurate water body management.

Satellite images has become a crucial tool for monitoring and managing the water resources or water bodies. The proper identification of waterbodies is critical for a variety of purposes. However, this assignment presents various difficulties due to elements like as differences in water, shadows, topographical characteristics, and the existence of different land cover categories.

Research Challenges in ResNet50 Water Body Segmentation for Satellite Images

- Detecting small water bodies.
- Handling class imbalance.
- Generalizing across environmental conditions.
- Integrating spatial context.
- Improving semantic segmentation performance.
- Addressing data annotation challenges.
- Data annotation is time-consuming.
- Scalability and efficiency are critical for efficient inference on large-scale imagery.

In conclusion, the project aims to deliver an advanced segmentation model based on the ResNet50 architecture capable of accurately segmenting water bodies in satellite images.

Figure1 shows different waterbody images from dataset are collected from Kaggle website.

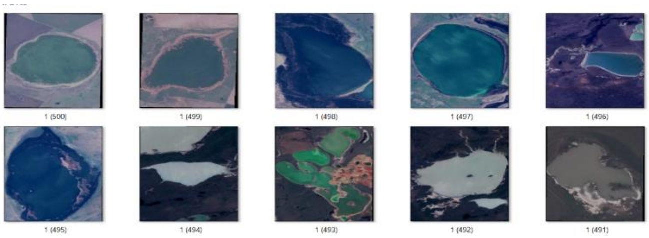


Fig 1. Different waterbody images from dataset

Water body segmentation in satellite image to monitor Drying of water bodies (like lakes, ponds etc) and constantly investigate the flooded aeras are the major uses of the work ResNet50. Further it is divided into following into sections, section 2 including previous work in the deep learning semantic segmentation field, section 3 has research methodology, system specifications, model implementation and in section 4 have dataset sources, sample images, and masks. Results and conclusion are discussed in sections 5 and 6.

2. Literature Review

In recent years, various algorithms have been developed to extract water bodies from remote-sensing images. Water body segmentation using deep learning, or any other deep learning method like convolutional neuralnetwork (CNN), lead to employing AI deep techniques to automatically locate and delineate water bodies from satellite imagery. Here's a literature review that summarizes several major studies in this field.

It is essential to monitor global environment because of climate changes, including lack of water. Satellite imaging and deep learning methods are utilized to create this process. Dmytro Filatov [5] proposes an image segmentation UNet model for observing forest and water areas. This innovative approach helps monitor the Earth's environment effectively. Ghulam Nabi Ahmad Hassan explains that U-Net operates on the encoder-decoder concept. Like encoders and decoders, it is divided into contraction at one side and an expansion at the other end. The contraction side denotes samples with maximum layers of pooling. The expansion section is a device called decoder and locates the semantic segmentation portion using transposed convolutional layers. The network is end-to-end, completely connected, with no thick layers.

Automatic detection of water body from the images by satellite is crucial for urban hydro-logical research. Kunhao Yuan [6], proposes a new Deep learning network Convolutional neuralnetwork model, the waterbody with multichannel area detection of the network (MC-WBDN) includes different innovative components, those are i. A multichannel fusion device.ii An improved Atrous Spatial Pyramid Pooling module, and iii. Space-to-Depth/Depth-to-Space operations. The model utilizes satellite data for successful water area recognition, utilizing its multispectral data for improved feature retention. The MC-WBDN architecture outperforms other estimated models, summing up traditional waterbody area detection process indicates and advanced deep learning in ai models based on RGB and multispectral input and shows enriched robustness beside light and weather distinctions.

Glaciallake mapping project is crucial for understanding climate change retort and risk assessment. Wang[7] explains that UNet, an AI based deeplearning method,it has potential, but inefficiently utilizes low-level features. A new standardized distinction water index (NDWI) attention U-Net (NAU-Net) is utilized for pixel-wise glacial lake segmentation. He explains that NDWI is a spatial attention, focusing more on water regions in low-level feature mappings.

MSR-Net is an innovative multiscale refinement network for water-body segmentation in high-resolution satellite imagery. Lunhao Duan [8] explains multiscale information in a new perspective, adopting a multiscale refinement scheme for more accurate segmentation. The network also features an erasing-attention module for effective feature embedding.

This paper provides an automatic B-snake technique for the adaptive boundary extraction of water in satellite images. Wenying Du [9] explains about areal images, covering various inner island members, waterbody different sizes, boundary or interface complexities, boundary or interface clarities and the background complexities. These four indices, including area overlap measure, correctness, completeness, and efficiency, were adopted to evaluate the performance of the B-snake, AB-snake, and OT-snake methods.

Surface water mapping is essential for remote sensing applications such as estimating water availability, measuring its changes over time and predicting droughts and flooding. Furkan Isikdogan [10] explains Landsat missions and Traditional Landsat water indices they require threshold values and suffer from false positives due to snow, ice and terrain misidentification. He explains the Deep-Water Map model, which is based on Landsat imagery, learns water body characteristics from global data. This paper has the formula that separates water from land, snow, ice, clouds, and shadows using only Lands at bands as input.

Remote sensing offers real-time, wide coverage, and rich information for water monitoring. H.Hafizi [11] examines universal methods of waterbody extraction using optical images and microwave radar images, which including different methods like threshold method, support vector machine etc. This paper explains that all methods can yield reliable results, with threshold segmentation method being more robust. Remote sensing offers real-time, wide coverage, and rich information for quick water information extraction.

Lingkui Meng [12] monitored water bodies and reservoirs by analysing micrographs from Google Earth pictures. They acquired Satellites photos related to Lake of Central Asia. They used GIMP to create a binary mask of the photos and Google Earth to compute the quantity of water in the lake based on elevation profiles.

Singh employed deep U-Net to segment various locations in satellite pictures, including highways, houses, and agricultural grounds. Nongmeikapam [13] emphasized the need of segmentation in promoting sustainable growth. They suggested Deep learning U-Net, this is a modified version of deep U-Net for this purpose. The purpose of this semantic segmentation technique is to identify land covers, evaluate their effectiveness and track changes over time.

Weng claimed that studying of climate changes needs monitoring of water bodies. Segmentation of water body images is a critical component in completing this assignment. shortcomings in existing algorithms were [14] identified by Xia.

3. Methodology

It is difficult to recognize water bodies in the large-scale remote sensing environment because their proportion to the total area is so small. Furthermore, detecting water bodies is difficult due to the poor contrast of the raw remote sensing image, which is impacted by mixed image elements. The proposed approach collects data and utilizes a deep neural network to partially address the issue. Proposed method implemented with Resnet50 to identify waterbody using semantic segmentation. Figure 2 shows the Resnet architecture.

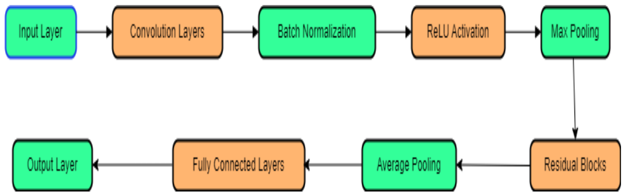


Fig 2. Block diagram of Resnet Architecture

Block diagram of Resnet consisting of multiple Convolutional layers with skip connections, Batch normalization, Activation function as Relu, Max pooling layer and Residual blocks, These blocks maintain the image plane resolution present in input feature maps, and the convolutional layers within each residual block extract feature information using learnable filters. Pooling layers can be used to downsample feature maps, reducing spatial dimensions and increasing the receptive field. Skip connections are crucial in image segmentation tasks, allowing the network to circumvent individual layers and propagate information from earlier to later layers. They facilitate the fusion of low-level and high-level features, enabling the decoder to create accurate segmentation masks for the satellite images. After the encoder, a decoder network is employed to gradually upsample feature maps to the actual input image resolution. Each up-sampled feature map along with data is concatenated and the subsequent feature map from encoder through skip the connections, allowing decoder to refine the segmentation output using both low-level and high-level data feature representations. The Final decoder output typically contains of a conventional layer with an appropriate activation function, creating the pixel-wise segmentation mask. ResNet's architecture, with its residual blocks and skip connections, serves as a efficient feature centrifuge in image segmentation models.

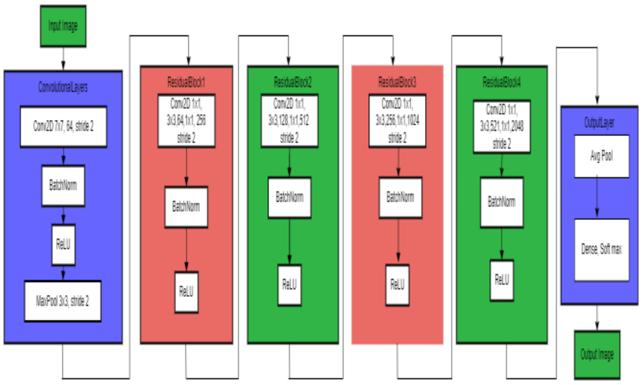


Fig 3. Resnet50 Internal Architecture

A deeplearning CNN (convolutional neural network) architecture, ResNet50 which was designed to address the challenges of training very deep networks. It have an Input layer, Initial layer of Convolutional layer and Batch normalization, Relu activation layer, Max pooling layer, Residual blocks, Average pooling layer, Fully connected layer (dense layer), and Output layer.

- The input layer accepts RGB images of size 224x224x3.
- The initial convolutional layer extracts basic details from the image.
- Batch Normalization enhances training stability and accelerates convergence by normalizing the activations of each layer across mini batch.
- ReLU is a widely used, efficient and non-linear activation function in neural networks, enabling the net to learn complicated or difficult patterns and relationships presented in the actual or original data.
  The Relu activation function is defined like this as f(x) = max(0, max)
- The max pooling layer reduces spatial dimensions while retaining important information.
- ResNet50 consists of 16 residual blocks organized into four stages, each with its own configuration of convolutional layers. Each block typically consists of three convolutional layers, including a bottleneck layer, which reduces the number of parameters and computational cost.
- The GAP or global average pooling layer which reduces the feature maps spatial dimensions to a vector by taking the normal of each feature map.
- The fully connected layer or dense layer is added after the global average pooling layer, typically having 1000 units and using softmax activation to produce the final classification probabilities.
- The output layer generates the final classification probabilities for the input image, containing as many units as the classes in the dataset and using softmax activation to output the probabilities.

Dividing dataset into training, validation and test sets. Train the ResNet50 model with the training set. The source images submitted to the Resnet network were 256x256x3. Accuracy, Loss and mean Intersection over Union coefficient were the matrices monitored during training. The binary cross-entropy function was employed in conjunction with a learning rate of 0.001. The Adam optimizer was utilized to optimize the performance of loss. For training, a batch of 32 was utilized, while for validation, a batch of 24 was employed. For training, 80% of the dataset was utilized, while the remaining 20% was used for validation. The model was saved if the minimal loss was met. The initial halting condition was also implemented due to validation loss. If the validation loss declines after nine successive iterations, the training model is terminated after that it is considered as good model and it is chosen with the same weights.

Algorithm of Resnet50 architecture for segmenting satellite image for waterbody

1. Input image

2. Preprocessing of data

3. Feature Map

4. Resnet 50 network

   a. Input layer

   b. Initial Convolution and MaxPooling

   Convolution1 and Maxpooling1

   - Convolution with 64 filters of 7x7, stride 2, padding 3.
   - Batch Normalization.
   - ReLU activation.
   - MaxPooling with a 3x3 filter, stride 2, padding 1.

   c. Residual Block1

   Convolution 2

   - Identity connection.
   - Main path
     - Convolution of 64 filters of size 1x1, stride 1, padding 0.

- Batch Normalization and ReLU activation are essential.
- Convolution with 64 filters of 3x3, stride 1, padding 1.
- Batch Normalization and ReLU activation are essential.
- Convolution with 256 filters of 1x1, stride 1, padding 0.
- Batch Normalization.

- Add shortcut and main path outputs.
- ReLU activation.

- Repeat the above main path (excluding the initial 1x1 conv layer in the first block) two more times with identity connections.

d. Residual Block 2

Convolution 3

- Identity connection.
- Main path
    - Convolution of 128 filters of size 1x1, stride 2, padding 0.
    - Batch Normalization and ReLU activation.
    - Convolution with 128 filters of 3x3, stride 1, padding 1.
    - Batch Normalization and ReLU activation are essential.
    - Convolution with 512 filters of 1x1, stride 1, padding 0.
    - Batch Normalization.
- Create shortcut and main path outputs.
- ReLU activation.

- Repeat the above main path (excluding the initial 1x1 conv layer in the first block) three more times with identity connections.

e. Residual Block3

Convolution 4

- Identity connection.
- Main path
    - Convolution of 256 filters of size 1x1, stride 2, padding 0.
    - Batch Normalization and ReLU activation.
    - Convolution with 256 filters of 3x3, stride 1, padding 1.
    - Batch Normalization and ReLU activation are essential.
    - Convolution with 1024 filters of 1x1, stride 1, padding 0.
    - Batch Normalization.
- Create shortcut and main path outputs.
- ReLU activation.

- Repeat the above main path (excluding the initial 1x1 conv layer in the first block) five more times with identity connections.

f. Residual Block 4

Convolution 5

- Identity connection.
- Main path
    - Convolution of 512 filters of size 1x1, stride 2, padding 0.
    - Batch Normalization and ReLU activation.
    - Convolution with 512 filters of 3x3, stride 1, padding 1.
    - Batch Normalization and ReLU activation are essential.

- Convolution with 2048 filters of 1x1, stride 1, padding 0.
- Batch Normalization.
- Create shortcut and main path outputs.
- ReLU activation.
- Repeat the above main path (excluding the initial 1x1 conv layer in the first block) two more times with identity connections.

g. Final Layers

- Average Pooling: Global Average Pooling (reduce each 2048-feature map to a single value).
- Fully Connected Dense layer : Dense layer with 1000 units (for 1000 classes in ImageNet), followed by a softmax activation.

5. Output: Segmented water body images

4. Results and Discussion

Experiments are performed for the segmentation of satellite images for waterbody by using collected images from Kaggle and simulated using Python software. The model used here is Resnet50 to segment water from satellite images. Figure shows the satellite image, mask and their histogram images.

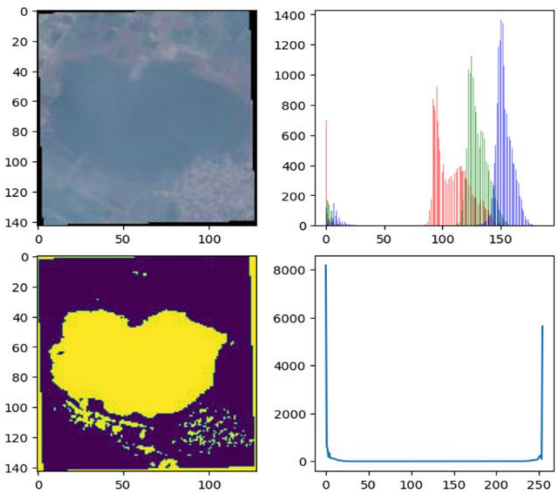


Fig 4. Input image, Mask and respective histogram images.

Evaluation Metrics:

Overall Accuracy

Overall accuracy is a evaluation metric used to calculate the effectiveness of segmentation methods. It determines the precise proportion forecasts the model generated for every image in the dataset. The range of overall accuracy is 0 to 1, where a greater number indicates good performance.

Overall Accuracy = (Number of correctly segmented pixels / Total number of pixels) x 100.

This is the evaluation metric for overall accuracy. An accuracy of 1.0 would suggest that every example in the dataset was correctly predicted, signifying a perfect model. While complete accuracy is a useful metric, it may not provide a whole picture of a model's performance.

Loss Function

The loss calculation involves comparing the model's predictions with the ground truth labels for a given set of input data. The ResNet50 model, commonly used for image segmentation tasks, employs a loss function called categorical cross-entropy loss. The choice of loss function depends on the task, and the goal is to minimize it to ensure accurate predictions and generalization to unseen data. This minimizes the loss function, indicating the model's ability to match ground truth labels and make accurate predictions.

This work utilized mIoU approximation and binary cross-entropy as loss functions, with mIoU approximation being used as a standard for evaluation metrics in semantic segmentation, and in some datasets binary cross-entropy for comparison.

Total Loss = $1\backslash N \sum_{i=1 \text{ to } N} L_i$

mIoU= Overall area/ Unin area

Analysis of Proposed (Resnet 50) model:

The Resnet50 model can be used to segment water body images, trained for epochs of 50 unless stopped by a defined criterion of stopping with learning rate of 0.001. The results may suggest that the Resnet model performance was better on the water bodies dataset. The learning curves of accuracy and loss curves for water bodies in satellite image datasets are shown in Figures 4 and 5.

Table 1: The Resnet50 dataset includes result matrices for water bodies.

Parameter/Method	Unet	Resnet50
Accuracy %	83.17	86.26
Loss %	23.07	31.97
Validation Accuracy %	82.92	96.02
Validation Loss %	23.85	20.12
mIOU %	60.22	74.99

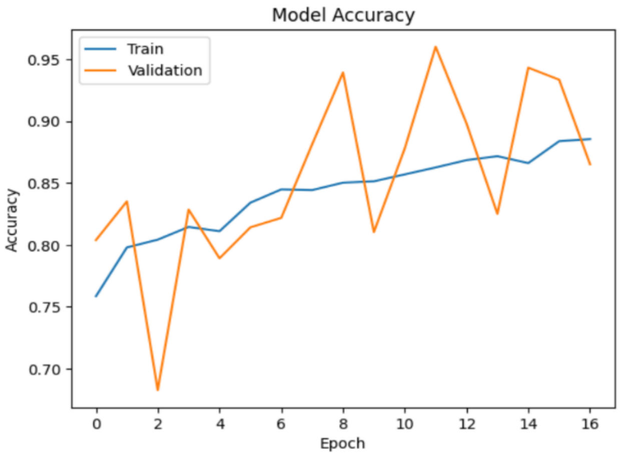


Fig 4. Accuracy verses epoch curve

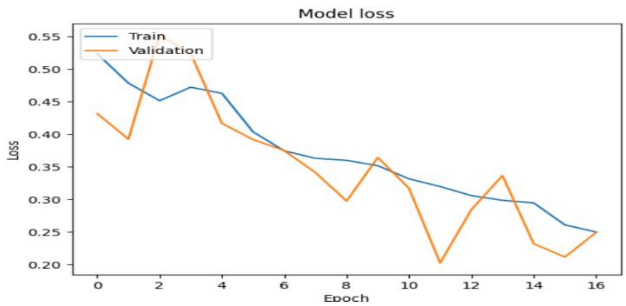
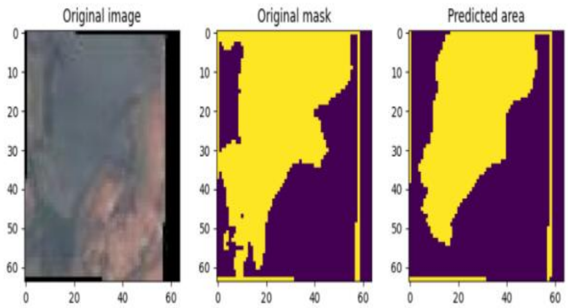


Fig 5: Loss verses epoch curve

The Resnet50 model was trained for 12 iterations on the water data set stopping at epoch 16 and maintaining no loss. However, it trained for all 50 epochs, demonstrating an increasing accuracy. The evolution of confirmation accuracy graph for water area dataset is increasing and then the loss curve for the water bodies dataset shows a decrease from the beginning. The final results for semantic data segmentation are presented in below Figure 6, demonstrating the original satellite image, ground truth image, and the predicted mask using Resnet.



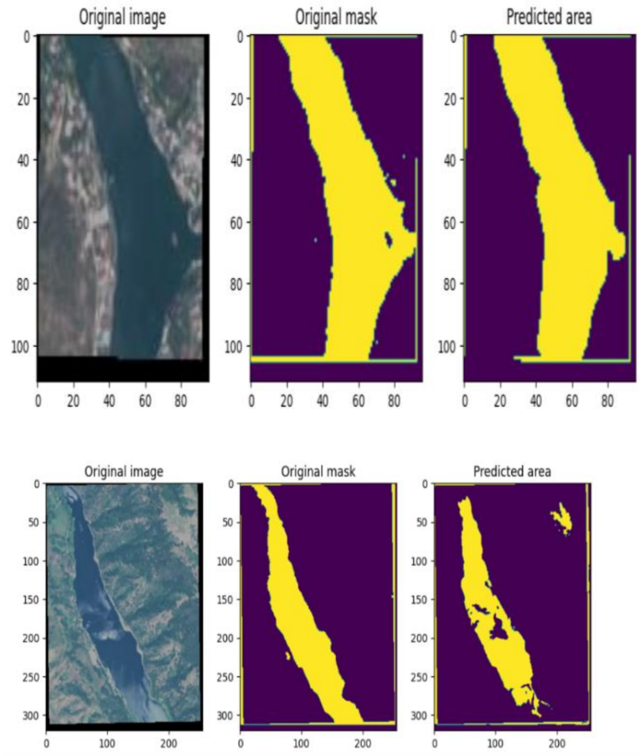


Fig 6. The Original image, Ground truth or Original mask, and Predicted area.

5. Conclusion

This work proposed using satellite imaging in water body segmentation using the Resnet semantic segmentation model, analysing its performance based on the obtained results. The proposed method for automatic monitoring of water segmentation process was found to be effective, despite a limited number of satellite images in the dataset, with reasonable results and accurate mean values measured for different random images, based on the Resnet model.

The suggested approach is effective and ideal for satellite picture segmentation. The Kaggle website provided the dataset used in this study. This method achieves the maximum accuracy of 96.02% when segmenting satellite pictures. Future work aims to create a multiclass system for satellite image segmentation that considers huge datasets with a higher sample count. Accuracy increases with the number of photos you capture.

References

[1] Silmie Vidiya Fani; Kamirul; Astriany Noer; Stevry Yushady CH Bissa,"U-Net Based Water Region Segmentation for LAPAN-A2 MSI", 2022 IEEE International Conference on Aerospace Electronics and Remote Sensing Technology (ICARES) , 30 December 2022.

[2] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in International Conference on

Medical image computing and computer-assisted intervention. Springer, 2015, pp. 234–241.

A. C. Sparavigna, “Image segmentation applied to satellite imagery for monitoring water in lakes and reservoirs,” PHILICA, Article, no. 1214, 2018.

[3] W. Alsabhan and T. Alotaiby, “Automatic building extraction on satel lite images using unet and resnet50,” Computational Intelligence and Neuroscience, vol. 2022, 2022.

[4] D. Filatov Ghulam Nabi Ahmad, Hassan Yar, “Forest and Water Bodies Segmentation Through Satellite Images Using U-Net”, Published in arXiv.org 12 July 2022,Environmental Science, Computer Science.

[5] Kunhao Yuan , Xu Zhuang, Gerald Schaefer and Jianxin Feng, “Deep-Learning-Based Multispectral Satellite Image Segmentation for Water Body Detection” ,IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing ,Volume: 14, pp. 7422 - 7434, July 2021.

[6] Jinxiao Wang ,FangChen, Meimei Zhang and BoYu, “A New Deep Learning Framework in Glacial Lake Detection” , IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, VOL. 19, pp. 20009052–9052, May 2022.

[7] Lunhao Duan and Xiangyun Hu, “Multiscale Refinement Network for Water-Body Segmentation in High-Resolution Satellite Imagery”, IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, VOL. 17, NO. 4, pp.686-690, APRIL 2020.

[8] Wenying Du, Nengcheng Chen, and Dandan Liu,” Automatic Balloon Snake Method for Topology Adaptive Water Boundary Extraction”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,Volume: 10, Issue: 12, December 2017.

[9] Furkan Isikdogan ,AlanC.Bovik,” Surface Water Mapping by Deep Learning”, IEEE Journal Of selected topics in applied earth observations and remote sensing, Vol. 10, NO.11, pp.4909-4918,NOVEMBER2017.

[10] H.Hafizi and K.Kalkan,“Evaluationofobject-basedwaterbodyextraction approachesusinglandsat-8 imagery,” J. Aeronaut. SpaceTechnol., vol.13, no. 1, pp. 81–89, 2020.

[11] Lingkui Meng, Zhiyuan Zhang, Wen Zhang, Jinan Ye And Chao Song, “An Automatic Extraction Method for Lakes and Reservoirs Using Satellite Images,” PHILICA, Article, no. 1214, 2018.

[12] N. J. Singh and K. Nongmeikapam, “Semantic segmentation of satellite images using deep-unet,” Arabian Journal for Science and Engineering, pp. 1–13, 2022.

[13] L. Weng, Y. Xu, M. Xia, Y. Zhang, J. Liu, and Y. Xu, “Water areas seg mentation from remote sensing images using a separable residual segnet network,” ISPRS International Journal of Geo-Information, vol. 9, no. 4, p. 256, 2020.

[14] Kaplan, G.; Avdan, U. Object-based water body extraction model using Sentinel-2 satellite imagery. Eur. J. Remote Sens. 2017, 50, 137–143.

[15] Anusha, C.; Rupa, C.; Samhitha, G. “Region based Detection of Ships from Remote Sensing Satellite Imagery using Deep Learning”. In Proceedings of the 2022 2nd International Conference on Innovative Practices in Technology and Management (ICIPTM), Pradesh, India, 23–25 February 2022; pp. 118–122.

[16] Erfani, S.M.H.; Wu, Z.; Wu, X.; Wang, S.; Goharian, E. ATLANTIS,”A benchmark for semantic segmentation of waterbody images”. Environ. Model. Softw. 2022, 149, 105333.

[17] Rajyalakshmi, C.; Rao, K.R.M.; Rao, R.R. Compressed High Resolution Satellite Image Processing to Detect Water Bodies with Combined Bilateral Filtering and Threshold Techniques. Trait. Signal 2022, 39, 669–675.

[18] K. He, X. Zhang, S. Ren, and J. Sun. „Deep Residual Learning for Image Recognition“. In: arXiv e-prints (2015). arXiv: 1512.03385.

[19] K. He, X. Zhang, S. Ren, and J. Sun. ‘Identity Mappings in Deep Residual Networks“. In: arXiv e-prints (2016). arXiv: 1603.05027.

[20] O. Ronneberger, P. Fischer, and T. Brox. „U-Net: Convolutional Networks for Biomedical Image Segmentation“. In: ArXiv e-prints (2015). arXiv: 1505.04597.

[21] Z.Zhang,Q.Liu,andY.Wang.„RoadExtraction by DeepResidual U-Net“. In: ArXiv e-prints abs/1711.10684 (2017). arXiv: 1711.10684.

[22] Kaiming Heetal.“Deep Residual Learning for Image Recognition”. In:CoRRabs/ . http://arxiv.org/abs/1512. 03385.

[23] O. Ronneberger, P. Fischer, and T. Brox, “U-Net: Convolutional networks for biomedical image segmentation,” in Proc. Int. Conf. Med. Image Comput. Comput.- Assist. Intervention, 2015, pp. 234–241.

[24] J. Long, E. Shelhamer, and T. Darrell, “Fully convolutional networks for semantic segmentation,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2015, pp. 3431–3440.

[25] X. Huang, C. Xie, X. Fang, and L. Zhang, “Combining pixel-and object-based machine learning for identification of water-body types from urban high-resolution remote-sensing imagery,” IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 8, no. 5, pp. 2097–2110, May 2015.

[26] M. Silveira and S. Heleno, “Separation between water and land in SAR images using region-based level sets,” IEEE Geosci. Remote Sens. Lett., vol. 6, no. 3, pp. 471–475, Jul. 2009.
[27] G. L. Feyisa, H. Meilby, R. Fensholt, and S. R. Proud, “Automated water extraction index: A new technique for surface water mapping using landsat imagery,” Remote Sens. Environ., vol. 140, pp. 23–35, 2014.
[28] S. Lu, B. Wu, N. Yan, and H. Wang, “Water body mapping method with HJ-1A/B satellite imagery,” Int. J. Appl. Earth Observ. Geoinf., vol. 13, no. 3, pp. 428–434, 2011.
[29] W. Feng, H. Sui, W. Huang, C. Xu, and K. An, “Water body extraction from very high-resolution remote sensing imagery using deep U-Net and a super pixel-based conditional random field model,” IEEE Geosci. Remote Sens. Lett., vol. 16, no. 4, pp. 618–622, Apr. 2019.