Deep Learning Techniques for Extraction of River Networks from Satellite Imagery

Dr. G. Malini Devi[1], Mrs. Radhika Chukkapalli[2], Dr. Raghavender K V[3], Mrs. S. Sandhya[4], Jageti Padmavathy[5], Dr. G. K. Srikanth[6], Dr. S. Kannan Shanmugam[7]
[1]Associate Professor, Department of CSE, G. Narayanamma Institute of Technology & Science, Hyderabad, India. Email: gmalini12@gnits.ac.in
[2]Assistant Professor, Department of CSE, G. Narayanamma Institute of Technology & Science, Hyderabad, India. Email: ch.radhika@gnits.ac.in
[3]Associate Professor, Department of CSE, G Narayanamma Institute of Technology and Science, Shaikpet. Email: drkvraghavender@gnits.ac.in
[4]Assistant Professor, Department of CSE, G. Narayanamma Institute of Technology & Science, Hyderabad, India. Email: s.sandhya@gnits.ac.in
[5]Assistant Professor, Department of CSE, G. Narayanamma Institute of Technology & Science, Hyderabad, India. Email: jpadmavathi@gnits.ac.in
[6]Assistant Professor, Department of CSE, AVNIET, Koheda Road, IBP. Email: drgksrikanth04@gmail.com
[7]Associate Professor, Department of Gaming Technology, School of Computing Science and Engineering, VIT Bhopal University, Sehore, Madhya Pradesh, India. Email: kannanshanmugam@vitbhopal.ac.in

ABSTRACT

Rivers play an essential role as coastal systems, supporting over 500 million people worldwide. Detecting and mapping water bodies through satellite imagery is crucial for disaster forecasting, monitoring droughts and floods, and managing water resources. However, current methods—including hydrological surveys, GIS,9 and various models—face challenges such as low satellite resolution, spectral inconsistencies, and the need for extensive ground surveys, all of which limit mapping precision. The proposed system introduces an innovative approach that employs a comprehensive dataset alongside deep learning models, specifically UNet and VGG16-UNet, tailored for image segmentation. While UNet captures detailed spatial and contextual information, VGG16-UNet leverages deep convolutional layers from VGG16 within UNet's architecture to enhance segmentation performance. Our objective is to create high-precision river network extraction models supported by an intuitive interface to facilitate automated detection and analysis, contributing to more informed decisions in river network monitoring.

Keywords: River Network Detection, Satellite Imagery, Deep Learning, UNet, VGG16 UNet, Image Segmentation, Disaster Prediction, Water Resource Management, Automated Detection, Coastal Systems

How to cite this article: Malini Devi G, Chukkapalli R, Raghavender KV, Sandhya S, Padmavathy J, Srikanth GK, Kannan Shanmugam S. Deep Learning Techniques for Extraction of River Networks from Satellite Imagery. Int J Drug Deliv Technol. 2026;16(20s): 982-992. DOI: 10.25258/ijddt.16.20s.99

Source of support: Nil.

Conflict of interest: None

I. INTRODUCTION

A. *Background of the Study*

Rivers are indispensable to life on Earth, acting as natural conduits that transport water and nutrients, support biodiversity, and shape ecosystems [12]. Historically, rivers have been central to human civilization, providing resources, fertile land, and routes for transportation. They regulate the water cycle, influence climate, and sustain wetlands and groundwater, creating habitats ranging from rapids to tranquil floodplains that support diverse species[14]. Human civilizations have always thrived along rivers, depending on them for drinking water, agriculture and transport. Fertile valley river systems gave rise to ancient civilizations such as those on the banks of the Nile, the Indus, and the Yellow Rivers, permitting agricultural and urban development. Rivers continue to be crucial open systems that support economic activities—irrigating agriculture, running industry, and powering hydroelectric generation—and provide recreational and aesthetic value for enhancing quality of life[18].

Preservation of ecological and socio-economic contributions of rivers can only be ensured by the conservation of rivers. Sustainable management includes pollution control, habitat restoration, and inter-sectoral cooperation to protect water quality and strengthen ecosystem resilience [15]. Sustainable management involves pollution management, bioregional restoration, and inter-sectoral collaboration to safeguard water quality and reinforce ecosystem resilience [15]. Rivers are essential to Earth systems, as they distribute water as well as sustain biodiversity and promote ecological muck. Rivers provide critical services, and accurate mapping of river networks is crucial for environmental monitoring, water management, flood risk assessment, and urban planning. River networks play a significant role in managing water resources as primary sources of freshwater. Efficient detection informs accurate, sustainable use, contamination monitoring of drinking water source protection are public health integrators [17]. River mapping is equally very crucial to flood mitigation by pinpointing high-risk areas and improve early warning systems for lower disaster impacts, the rivers are the lifeline of all.Rapid urban growth means incorporating river data into planning to provide adaptive cities as urban flooding resilience infrastructure and reduce environmental destruction that mitigate stormwater management deliverable against climate change.

River network detection is essential for hydrology, geomorphology and environmental science. Remote sensing and deep learning before provide advances limited to high-resolution mapping for river genesis and natural interactions [13]. This understanding not only improves the scientific knowledge but it is also valuable for policies for effective resource management. Real time monitoring of rivers during natural disasters such as floods and hurricanes is critical for firstly informing evacuations, secondly to allocate resources to prevent damages. Accurate mapping also facilitates recreational planning, ensuring enjoyment of river areas in a controlled and sustainable manner via responsible tourism, contributing to local economies and conserving natural resources. River networks are essential for irrigation and water distribution in agriculture. By mapping these networks, irrigation efficiency improves, drought mitigation and flood prevention are enhanced [16], so farmers can better manage their water resources and apply conservation measures to enable sustainable agriculture.

II. LITERATURE SURVEY

This research extends the work of Ghaznavi et al., (2024), that compare and contrast three U-Net-based models in segmenting inland water bodies [2]: simple U-Net, Residual Attention U-Net [3], 952VGG16-U-Net. Their results indicated that VGG16-U-Net model works with a large segmentation accuracy and lesser computation expense of the previously proposed U-Net [1], due to that the introduced feature extraction strategies make extremely feature efficient [2]. With this base, the paper under consideration addresses two of our models for detecting river networks namely: UNet and VGG16-UNet. Based on the GitLab repository of Ghaznavi et al., this project takes a step further their workflow and adds a developed graphic user interface (GUI). GUI allows interaction changeover in showing segmentation results and results henceforth makes it much easier to use the models for practice in river monitoring or management. This is associated with the use of remote sensing in water body detection and characterizing ecological patterns, yet discerning small water bodies is not as easy as it may seem. The high accuracy (89% mean accuracy on boundaries and area/count water bodies) was achieved using deep learning for use on ISRO's Cartosat-3 images [26]. Such approach helps to detect small vegetated objects up to CMOS pixel resolution, but it requires huge data annotation and computational resources with some environmental restrictions [4].

In the water body extraction from remote sensing images, it frequently involves the extraction of fine details. Over 82% accuracy can be achieved by combining U-Net with two Deep Convolutional Neural Networks (DCNNs) in a deep learning model [2] that used DCNN for feature extractor and U-Net that perform pixel-level segmentation to map the urban areas for understanding details like shadows, vegetation and roads [2]. The traditional methods of segmentation lose spatial information and thus parameters inaccuracy. This initiative fills the above-mentioned gap by fusing in a convolutional network with dual-path UNet and ResNet-50, (also the Enhanced Mountain Gazelle Optimization; EMGO-Algorithm [1]. When tested on Indian Pines & Salinas datasets with hyperspectral images, (tested methods for other datasets: the SFnet-DA network that adopt a domain adaptation and a spatial self-attention (SSA)mechanism together with multi-scale feature fusion (MFF) is network [3]. Remote sensing images overlay we need to find proper edges and a lot of label samples so as to extract water bodies of all sizes. SFnet-DA network is composed of domain adaptation (DA) as well as a selective self-attention (SSA) module and a multi-scale feature fusion (MFF) module. With SSA and MFF, they provide spatial detail coherent semantics as well as accurate edge commitment.SFnet-DA uses an adversarial approach to apply labeled data for unlabelled predictions, outperforming existing segmentation models [5].Reliable water body detection is essential for disaster prediction, drought and flood monitoring. A study with 2841 Sentinel-2 images used UNet and TensorFlow for high-accuracy detection (94%) with a Nadam optimizer and secure data handling. While accurate, this approach faces obstacles like computational intensity, extensive parameter tuning, and reliance on high-quality data. Limitations also exist in datasets that miss rivers narrower than 30 meters, affecting river flow characterization [10].For river network mapping, a novel automated approach achieved 10-meter monthly resolution using Sentinel-1 SAR, Sentinel-2 multispectral images, and the AW3D30 DSM, with 95.8% accuracy. This generated a 40,280 km Yellow River network map, covering small to medium rivers. Monthly geometry data correlated with precipitation, offering a cost-effective, high-accuracy solution for global river mapping, though integration complexity and computational needs are high [11].River networks support resource management and flood monitoring. Using Kaggle and Google Earth Engine data, a study employed segmentation techniques, including grey scaling, global thresholding, and UNet architecture, achieving an 80.98% Dice score, confirming UNet's effectiveness in river extraction [7].Surface water monitoring with high-resolution remote sensing is challenging due to unclear water boundaries and high parameters. DeeplabV3+ was enhanced with MobileNetV2, a Channel Attention (CA) module, Atrous Spatial Pyramid Pooling (ASPP), and Focal loss, improving segmentation accuracy and efficiency. Results showed a 3.06% higher mean Intersection over Union (mIoU) than U-Net, outperforming MACU-Net and traditional DeeplabV3+ [8].Detecting surface water bodies is essential across applications. One study validated a Quadtree algorithm with fractal dimension on OpenAerialMap images, achieving 96.03% accuracy in surface water detection. This efficient method, while computationally simple, faces challenges with heterogeneous landscapes and spectral similarities [6].Small water bodies (<0.01 km^2) contribute significantly to Earth processes like carbon cycling. Using 3 m optical imagery from Planet Labs, a study mapped seasonal pond and lake variations across Alaskan regions, revealing substantial changes in snow-free periods that affect methane emissions. Online high-resolution monitoring can identify minute water bodies but the deep learning and data processing requirements are complicated [9].

III. METHODOLOGY

Implementing different parts of this project is what helps to Surf accurately river network using Deep learning Model.

A. Data Pre-Processing& Augmentation

A setup of a raw image dataset retrieved from the Google Earth Engine JavaScript (GEE) with the Sentinel-2 Harmonized. The images were from a prior project tackling to look into the simple U-Net, residual attention U-Net and VGG16-U-Net results for inland water body classification as mentioned in their publication/GitLab. Dataset used by this study is available in GitLab repository with the name "UNet based methods for Inventory Inland Water Bodies using remote sensing".

Sentinels-2 images are pre-normalized to set same color pixel values so that — the pixel values across all the images are standardized. Also, overlays are overlayed based on manually annotated masks to ensure clarity, and better detection of features that river networks are reliant on. To make the training data more diverse, we use data augmentation techniques to be able generalize well to driven by data. During model building this is done with the ImageDataGenerator and contains augmentation like rotation, flipping zoom and shifting so we obtain more robust dataset. Additionally real time augmentation to provide changing training samples at training time so that the model keeps progressing through different data stream at each training iteration.

B. Proposed Architecture

In this study, the proposed architecture introduced two deep learning models UNet and VGG16-UNet for segmentation. The UNet architecture with skip connections of the encoder-decoder type enables localization accuracy, as detailed river segmentation requires high-resolution data combined with context features output by UNet. VGG16-UNet combine the attention on spatial detail preservation in UNet with feature extraction capabilities of VGG16. Evaluated by metrics related to pixel classification such as accuracy, precision, recall and coverage against the ground truth to evaluate the detection quality. Last, the model is validated and tested, GUI is developed for Interactive demonstration on original satellite images of river network detections.

i *UNet Model*

UNet model architecture, widely used for image segmentation is outstanding in detecting intricate structures (river network in our case). As we will see in further detail, the model is designed following an encoder-decoder model in which both Contracting Path (Encoder) as well Expansive Path (Decoder) cooperate to model a combination between contextual information and spatial for accurate segmentation. The model in the Contracting Path (Encoder) receives 512×512 input images with three color channel (RGB) at first. Next, we have the first convolution block where two 3x3 convolutions with Leaky ReLU activations produce 64 feature maps and then the output is reduced spatial dimensions to 256 x 256 using a 2x2 max pooling.

The same paradigm repeats in the subsequent layers: second block will result in 128 feature maps of size 128 x 128, third 64 x 64 with 256 filters and last one is at 32 x 32 with 512. Embedded within the heart core of this model there is a bottleneck layer that multiplexes two 3x3 convolutions with Leaky ReLU activations to a depth of 1024 feature maps. These layers capture the different levels (feature hierarchies) of complexity, which enables the model to learn fine details and structures in the data.

While training, backpropagation fine-tunes these layers to achieve minimal loss on the train batch and making them segment correctly and generalize to new data. The ***Expansive Path (Decoder)*** reconstructs the spatial details lost during encoding. In the first up-convolution block, up-sampling increases dimensions from 32x32 to 64x64, and feature maps from the encoder path are concatenated with these up-sampled maps. This is followed by two 3x3 convolutions, resulting in 512 feature maps. In subsequent blocks, the decoder doubles dimensions and reduces feature maps as follows: the second block up-samples to 128x128 with 256 feature maps, the third to 256x256 with 128 feature maps, and the fourth to 512x512 with 64 feature maps. Finally, the output layer uses a 1x1 convolution to reduce the feature maps to a single class, generating a 512x512 binary mask that delineates river networks. This decoder structure refines the segmentation, allowing the model to recover precise spatial details and produce highly accurate predictions for river segmentation.

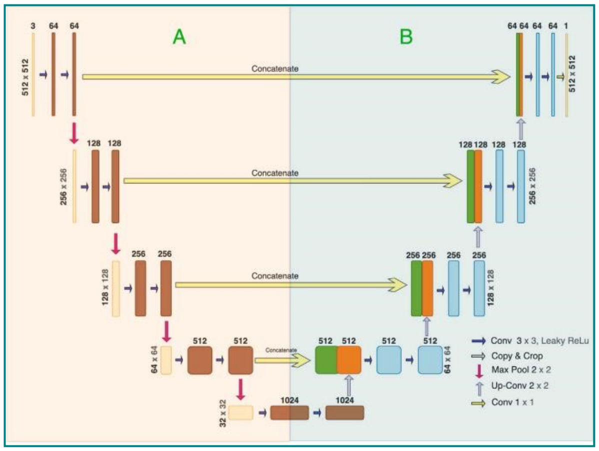


Fig 1. Architecture of UNet

The UNet architecture (Fig 1), initially designed for biomedical segmentation, is well-suited for detecting river networks. Its encoder-decoder structure uses a contracting path to capture contextual features and an expansive path to reconstruct spatial details, with skip connections allowing precise localization. This setup enables effective segmentation of complex structures, even with limited data, and is widely adaptable across various image segmentation tasks.

ii *VGG-16 UNet Model*

The VGG16-UNet model is an adaptation of UNet that integrates the VGG16 network as its encoder, combining VGG16's strong feature extraction with UNet's segmentation capability of VGG16 as an encoder in the VGG16-UNet model improves classical UNet with better feature extraction and segmentation outcome. The architecture is in a style of an Encoder-decoder framework with skip-connections enabling the model to preserve the local spatial details necessary for the proper segmentation of fine structures such as river networks. A Contracting Path (Encoder) starts by taking 512*512 RGB input model. Successive filters of 3 × 3 and activation layer (ReLU) with max-pooling convolutions to successively decrease spatial dimensions but increase depth feature map. First convolutional block gives 64 feature maps, down-sampling the spatial dimensions to be 256x256. From there in each subsequent block doubling the number again to produce 128, 256 and then 512 feature maps, we halve the dimensions down to 128 x 128, 64×64, then just to 32×32. The final block maintains 512 feature maps, further reducing dimensions to 16 x 16. This hierarchical structure allows the model to capture essential feature representations at multiple scales, laying a strong foundation for precise segmentation in the up-sampling path.

At the network's deepest point, the ***Bottleneck Layer*** holds the most abstract features, providing a condensed representation of the input image. This layer includes two convolutional layers, each with 512 filters, followed by dropout and batch normalization to reduce overfitting and ensure stable learning. These layers serve as a bridge between the encoder and decoder, enabling a smooth transition to the expansive path.The ***Expansive Path (Decoder)*** reconstructs high-resolution feature maps from low-resolution representations through a series of up-convolutions that double the spatial dimensions. In each up-convolution block, the upsampled feature maps are concatenated with corresponding feature maps from the contracting path, preserving spatial details and enhancing localization accuracy. This path includes two 3x3 convolutions with ReLU activations in each block, generating progressively fewer feature maps: 512, 512, 256, 128, and 64 filters. The final output layer applies a 1x1 convolution with a sigmoid activation to create a binary probability map, effectively highlighting river networks.***Skip Connections*** link each encoder block with the corresponding decoder block, ensuring that spatial details lost during down-sampling are reintroduced during up-sampling. These connections enhance the model's ability to precisely localize and segment river networks, producing more accurate and refined predictions.

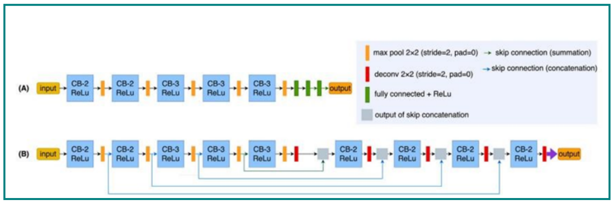


Fig 2. Architecture of VGG16 and its variants. (A) shows the standard VGG16 network architecture, while (B) illustrates the VGG16-UNet architecture.

As illustrated in (Fig 2), the model supports two architectures for segmentation tasks: Architecture (A) employs basic encoder-decoder layers with ReLU activations, max pooling for down-sampling, and deconvolution layers for up-sampling, maintaining spatial detail with skip connections. Architecture (B) enhances this structure by adding skip connections that concatenate feature maps, improving information flow and spatial preservation across the network.

C. *Training Models*

The methods were implemented on a computational platform equipped with CPUs, RAM, and GPUs. The dataset was divided into 80% for training, 20% for testing, with a validation set to prevent overfitting. Images were resized to a standard input size, and data augmentation was applied. Early stopping with specific parameters helped mitigate overfitting, while a pixel-level classification task enabled semantic segmentation. Dice Loss and Binary Focal Loss functions optimized the model's performance in distinguishing water bodies.

$$Focal\ loss = -\alpha_t^{\gamma(log_{1-pt})}(pt) \tag{1}$$

As shown in(1), focal loss was calculated as is the predicted probability for the true classy = 1, α_t is the weighting factor, and γ is the focusing parameter. Focal loss achieved better segmentation (see elaborate regions like water bodies that are narrow or textured backgrounds vs easier ones) by itself.

D. *Graphical User Interface (GUI)*

Graphical User Interface (GUI) — user interface that is developed for this project — is the primary way to interact with deep learning models for the the visualization of river network segmentation results. Driven in Python the GUI uses some libraries to push its functionality as well provide an easy-to-use interface for the user. The GUI was built using Python built-in libraries such as Tkinter (standard GUI library) to make Windows, Dialogs and other interactive elements that is necessary for user to navigate. The library OpenCV(Python) — an open-source computer vision library was used to get image processing work done on satellite images, included in it are methods for loading images, displaying and some basic manipulations to ease the user vision. TensorFlow and Keras Python libraries were used for real-time segmentation, as both models can be easily integrated to the GUI. The model has users provide with a satellite image that directly shows segmentation use-cases in real-time, with DL models doing the heavy lifting and outputting results immediately. The integration of these libraries in Python unified a more fluent and faster interface therefore providing user closer access to model functionalities complex and reducing the complexity of reading segmentation outputs.

IV. RESULTS AND DISCUSSION

A. *Performance Measures*

It is crucial to judge the performance of segmentation model for accurate river network detection. What key metrics tell you in a nutshell about the pros and cons (models)

Accuracy: Denotes the amount of pixels classified correctly in comparison to all pixels in the whole dataset (all-metric-over-all).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (2)$$

Precision: Indicates the percentage of true positive among predicted positive as so in indication on how reliable the model will classify things as positive.

$$Precision = \frac{TP}{TP + FP} \qquad (3)$$

Recall (Sensitivity): Tests just how good the model actually is at getting all the real positive instances right, like it correctly recognizing river pixels.

$$Recall = \frac{TP}{TP + FN} \qquad (4)$$

F1 Score: It provides a balanced measure between precision and recall, as it is the harmonic mean of both — thus offering you an accuracy reflection of the positives classified by your model.

$$F1\,Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \qquad (5)$$

Intersection over Union (IoU): IOU is the Measure of the overlap between predicted segmentation and ground truth and that helps with our model performance on reality dataset.

$$IoU = \frac{TP}{TP + FP + FN} \qquad (6)$$

Dice Coefficient; — More responsive to the small size objects compared with IoU, this metric is mostly used to evaluate segmentation quality particularly small features.

$$Dice\,Coefficient = \frac{2 \times TP}{2 \times TP + FP + FN} \qquad (7)$$

As a consequence, these performance metrics are key to measuring the success and trustworthiness of river network detection models segmentation. Every metric has its own role: Accuracy gives you a general idea of good classifications, while Precision and Recall help us understand if our model can suppress false positives and false negatives. The F1 score is suited to cases where one of Precision or Recall may be of more value than the other. IoU and Dice Coefficient are particularly useful to measure the spatial overlap of segmentation as i.e. verifying that predicted river networks are taxing very close to actual river boundaries. By pooling these metrics, we obtain a holistic and finely detailed model performance story-a basis for justified model selection as well as automatic detection of segmentations defects in a wide set of applications ranging from environmental monitoring to urban planning.

B) *Performance Comparison*

The subsequent arm of research implemented the rest of the performance records against UNet and VGG16-UNet in comparison.

TABLE 1 PERFORMANCE OF UNet vs VGG16-UNe

UNet Model		**VGG16-UNet Model**	
Evaluation Parameter	***%***	***Evaluation Parameter***	***%***
Recall	91.7716%	Recall	98.7349%
Precision	92.8081%	Precision	97.6803%
Accuracy	96.6741%	Accuracy	97.6754%
F1-Score	92.2695%	F1-Score	98.1898%
IoU	93.6179%	IoU	96.4582%
Dice	94.2695%	Dice	98.1898%

An 80–20 train-test split is used to compare the performance of the UNet and VGG16-UNet models for river network detection in TABLE 1. In terms of all metrics, the VGG16-UNet outperforms the UNet and it has higher values that are; Recall (98.73%) Precision (97.68%) Accuracy (97.67%) F1-Score (98.19%), Intersection over Union (96.46%), Dice Coefficient of the last column (98.19%), respectively. This, indicating that the feature extraction capabilities of VGG16 helps to improve the quality of river networks segmentation and hence better detection results than in the common settings UNet architecture.

C) *Comparative Analysis of Results*

Confusion Matrix: A table in which the performance of a classification model is evaluated showing true positives, true negatives and false positives/negatives. It gives extensive insight on the types of errors that the model tends to make, in addition to just how accurate it is. The confusion matrix helps identify the model's classifying skills per values, which is useful in tuning and optimizing classification accuracy by examining values computed from the matrix.

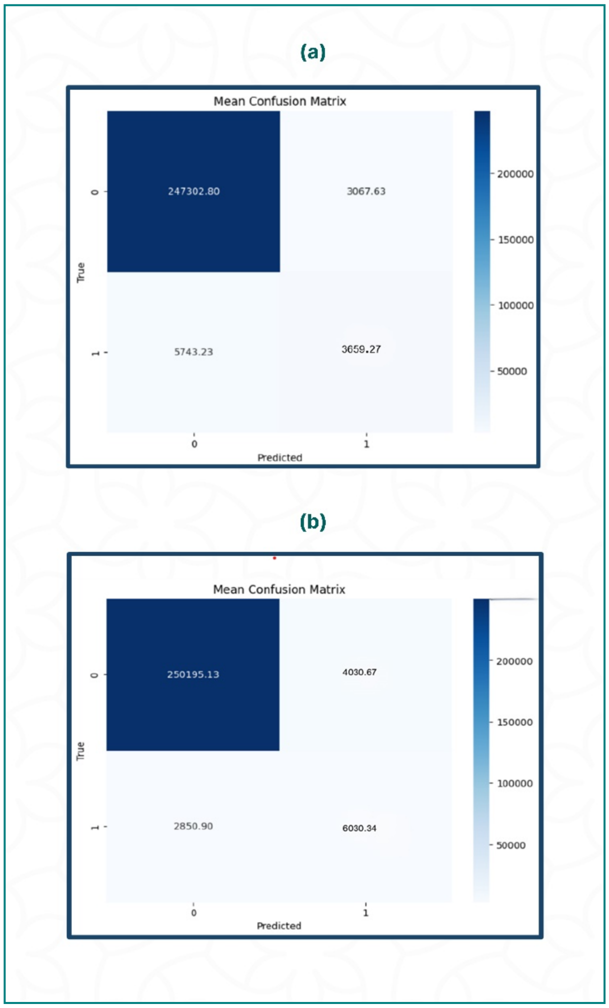


Fig 3Comparison of the Confusion Matrix: (a) UNet Model, (b) VGG16-UNet Model

When looking at (Fig 3) (a), a high number of true positives (247,302.80) and true negatives (3,659.27) shows that overall accuracy of UNet model is high. Nevertheless, there are significant false negatives (5,743.23) and false positives (3067.63) being identified which would suggest ways to refine, especially in decrease incorrect classifications. (b) Confusion matrix of the VGG16-UNet model (Fig 3) as an improvement in prediction capability.With increased true positives (250,195.13) and true negatives (6,030.34), and reduced false negatives (2,850.90) and false positives (4,030.67), the matrix reflects better sensitivity and specificity.

This comparison highlights the VGG16-UNet model's superior capability in accurately detecting river network features, reducing misclassification, and improving overall model reliability.

Receiver Operating Characteristic (ROC Curve)

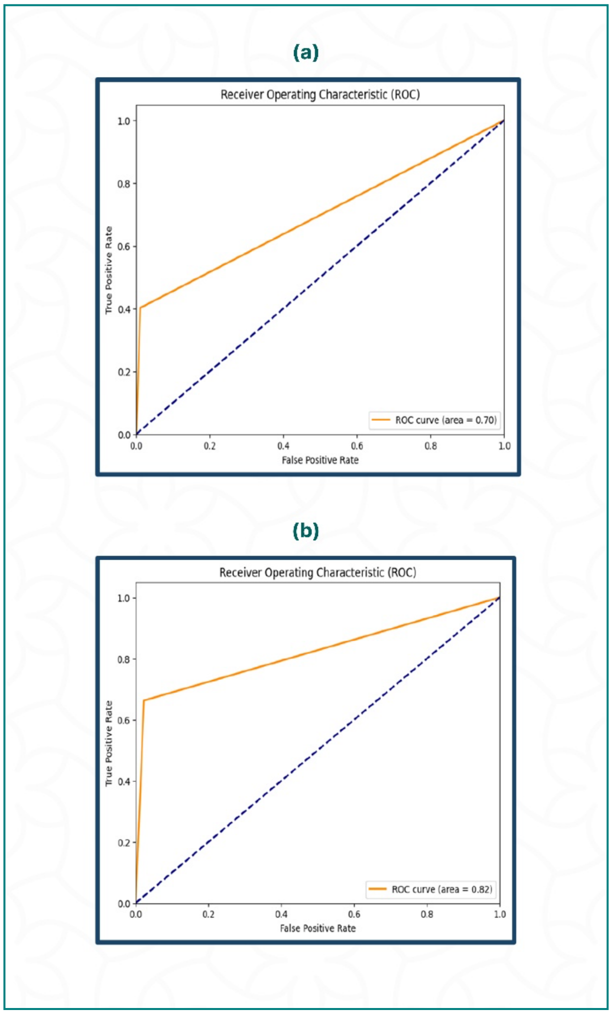


Fig 4. Comparison of the ROC Curve: (a) UNet Model, (b) VGG16-UNet Model

The (Fig 4) (a) indicates the ROC curve for UNet model having area under curve (AUC) =0. 798.This AUC value suggests the model has reasonable discriminative capability, though the curve could be closer to the top left corner for enhanced performance.In (Fig 4) **(b),** the ROC curve for the VGG16-UNet model achieves a higher AUC of 0.821, reflecting improved performance. A straighter curve to the upper left corner indicates that the model has an improved true positive rate over false positive rate—— predictive accuracy is simply stronger.

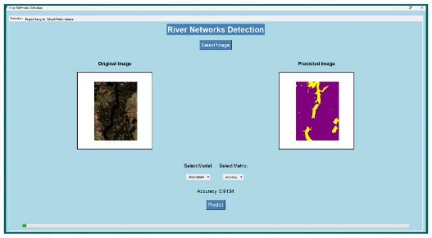
D) River Networks Detection

A custom GUI for the interactive use of trained model was developed GUI design for River Networks

Detection systems provide users with a friendly and convenient way to explore river networks. User-friendly interface that enables users to quickly and easily choose an image to be processed by the selected deep learning model The two models (UNet and VGG16-UNet) can be easily switched via drop-down menu to offer the user for fast model choice in prediction.

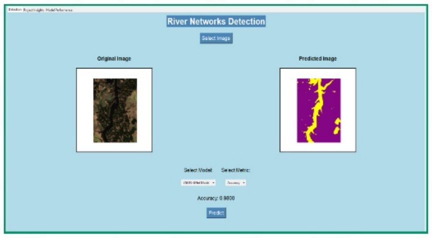
Furthermore, GUI contains additional factors for detailed posterior of the model performance such as precision, recall and f1-score, dice coefficient, Intersection over Union (IoU) to choose from. The GUI has also a part of the GUI called "Model Performance" tab where users can find graphs for different performance. This tab will have choices to visualize the metrics like training and validation loss, accuracy confusion matrices as well as ROC curves for both models, helping users understand effectiveness of each river network detecting model. The GUI also shows prediction results by superimposing the original image and river network predicted on top of other models for evaluation, complementary image segmentation quality. As always, VGG16-UNet gets to display with the higher accuracy in predictions producing a broader understanding of found rivernetworks.

(a) UNet



Accuracy: 0.9134

(b) VGG16 - UNet



Accuracy: 0.9800

Fig 5UNet (TOP) and VGG16UNet (BOTTOM) captured through GUI.

(Fig 5) (a) shows the output prediction of the UNet model, the left image is the ground truth and right is the obtained result by UNet network showing an accuracy of 91.30%. Fig 5) (b) VGG16-UNet results visualize original images with obtained predictions, a better accuracy 93.00%. This contrast shows how well VGG16-UNet works for identifying river networks.

(Fig 6) In addition provides an in-depth visualization comparison of output from both UNet and VGG16-UNet on the same original images.This side-by-side analysis highlights differences in the accuracy and precision of each detection method. Red and blue circles indicate key differences on the corresponding images of where the models disagree in determining river networks from red circles/particularly blue squares. These marks are meant help discern specific regions for areas where VGG16-UNet model will be able to retrieve finer details or provide more precise segmentation compared to classical UNet demonstrating the power of VGG16-UNet in feature extraction for improved segmentation quality.

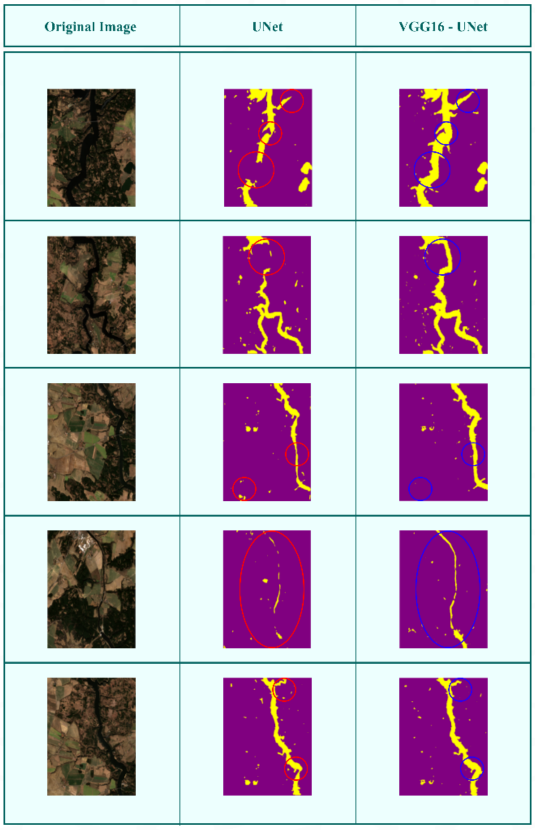


Fig 6. 5 Outcomes of UNet and VGG16-Unet on same original image compared.

Detailed comparison of the outcome between UNet and VGG16-UNet provides a better idea on which model can capture these subtle river boundaries and high dynamic features for more robust segmentation, thus refining river network mapping in varied terrain conditions.

V. CONCLUSION

Deep learning models are now adept at river network detection in satellite images, bringing huge gains to both accuracy of segmentation and model performance via its deployment and refinement. The VGG16-UNet, through the results of this comparative study shows that in fact is vastly superior architecture than the classic UNet, suggesting that it is at the forefront of river network segmentation methods. The VGG16-UNet got an amazing recall of 98.73%, which is far superior to the UNet recall 91.77% — meant to highlight its performance in properly detecting river pixels without false negative. In addition, the model showed quite amazing value at precision of 97.68% on average — in the very least out-performing UNet by more than two-fold and clearly capable of generating accurate prediction lines that do not succumb easily to false positives. Together, these metrics represent the VGG16-UNet model that is so superior that it becomes an immensely high-precision tool for river network detection which has massive impacts on environmental monitoring/water resources/ecological research. Not only that it's applied to static segmentation but we can certainly push this model's capability by future improvements which may be in targeted way. One possible improvement is dataset expansion. The model could be further generalized to deal with other kinds of images and different geographically, climatically conditions by incorporating a larger dataset. Perhaps integrating other model architectures (ResNet, DenseNet – both infamous for their deep feature extractors) into the model could in turn act as potential super-charger in order to improve the performance.Also, exhaustive hyperparameter tuning via grid search or Bayesian optimization may expose the best parameters set that will lead to an improved model accuracy and segmentation efficiency. A possible avenue for future research is the addition of temporal data to account for seasonal changes in river networks, allowing the model to adapt and provide insight into changing trends in river morphology, sediment transport and water flow. Temporal analysis of this kind would change the game in flood risk assessment, ecosystem monitoring and climate studies by giving us a longitudinal understanding of river network dynamics. To be immediately operational and able to handle real-time data which also would have an immediate data processing and analysis would deploy the model on cloud infrastructures making it a must-have in emergencies like flood forecasting or relief work. Improvements to the graphical user interface (GUI) of the system, regarding user-friendliness and specific interface design would improve system usability which later would made it applicable for a large population especially non-expert user who access systems (i.e, users from environmental agencies or research institutions). To extend river segments with additional spatial context or guidance (accordingly more accurate delineation), incorporating ground up remote sensed data layers (i.e., digital elevation models and land cover classifications) will be beneficial to segmentation. Moreover, more complex data-augmentation methods can be used to increase the robustness of models across different imaging conditions like changes in sunlight, cloud cover, and seasonal variations. Introducing hydrologic data (e.g., flow rate and water quality metrics) would bring another layer to this additional holistic system which could support multi-dimensional analyses that enable integrated water resource management.

Overall, the above listed improvements could turn this river network detection model to a versatile and advanced instrument for a wide range of scientific areas, policy-making applications, and resource management in environmental science. By advancing the state-of-the-art in river network segmentation, this research contributes meaningfully to the sustainable management of aquatic ecosystems, supporting conservation efforts, and equipping stakeholders with actionable insights for effective environmental stewardship.

ACKNOWLEDGMENT

The authors are grateful to their institute for the facilities and support that made this research possible. Special thanks to the department leadership and research mentorsfor their guidance and encouragementand support throughout the project.

REFERENCES

[1] Ali Ghaznavi, Mohammadmehdi Saberioon, Jakub Brom, Sibylle Itzerott, "Comparative performance analysis of simple U-Net, residual attention U-Net, and VGG16-U-Net for inventory inland water bodies", Applied Computing and Geosciences, Volume 21, 2024. https://doi.org/10.1016/j.acags.2023.100150.

GitLab - https://git.gfz-potsdam.de/ali/remotesensing-hida

[2] Anusha Ch, Rupa Ch, Samhitha Gadamsetty, Celestine Iwendi, Thippa Reddy Gadekallu, Imed Ben Dhaou. "ECDSA-Based Water Bodies Prediction from Satellite Images with UNet". Water, Vol. 14, pp. 2234, July 2022.

[3] Andrew L. Mullen, Jennifer D. Watts, Brendan M. Rogers, Mark L. Carroll, Clayton D. Elder, Jonas Noomah, Zachary Williams. "Using High-Resolution Satellite Imagery and Deep Learning to Track Dynamic Seasonality in Small Water Bodies". Geophysical Research Letters, Vol. 50, e2022GL102327, July 2023.

[4] Devang Jagdale, Neil Bhutada, Sukrut Bidwai, Sukhada Bhingarkar, Tejas Hiremath. "Extraction of River Networks from Satellite Images using Image Processing & Deep Learning Techniques". 2022 International Conference on Advancements in Smart, Secure, and Intelligent Computing (ASSIC), IEEE, Vol. 1, pp. 1-8, 2022.

[5] Ida Wahyuni, Wei-Jen Wang, Deron Liang, Chin-Chun Chang. "Rice Semantic Segmentation Using Unet-VGG16: A Case Study in Yunlin, Taiwan". 2021 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS), Vol. No. 2021, pp. 1-6, December 2021.

[6] Javier Del-Pozo-Velázquez, Pedro Chamorro-Posada, Javier Manuel Aguiar-Pérez, María Ángeles Pérez-Juárez, Pablo Casaseca-De-La-Higuera. "Water Detection in Satellite Images Based on Fractal Dimension". Fractal and Fractional, Vol. 6, pp. 657, November 2022.

[7] Jiahang Liu, Yue Wang. "Water Body Extraction in Remote Sensing Imagery Using Domain Adaptation-Based Network Embedding Selective Self-Attention and Multi-Scale Feature Fusion". Remote Sensing, Vol. 14, pp. 3538, July 2022.

[8] Jit Mukherjee. "Identifying Rivers with Varying Width Through NDWI from Landsat 8 Images". 2023 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Vol. No. 2023, pp. 3734-3737, July 2023.

[9] Junkai Huang, Xianliang Jiang, Guang Jin. "Detection of River Floating Debris in UAV Images Based on Improved YOLOv5". 2022 International Joint Conference on Neural Networks (IJCNN), Vol. No. 2022, pp. 1-6, July 2022.

[10] Mina Talal, Alavikunhu Panthakkan, Husameldin Mukhtar, Wathiq Mansoor, Saeed Almansoori, Hussain Al Ahmad. "Detection of Water-Bodies Using Semantic Segmentation". 2018 International Conference on Signal Processing and Information Security (ICSPIS), Vol. No. 2018, pp. 1-6, December 2018.

[11] Namdeo Baban Badhe, Vinayak Ashok Bharadi, Nupur Giri, Sujata Alegavi, Shashank S. Tolye. "An Efficient Image Segmentation using Optimized Segmentation Network for Remote Sensing Satellite Images". International Journal of Intelligent Systems and Applications in Engineering (IJISAE), Vol. 11(9s), pp. 804-821, 2023.

[12] Peng Li, Yun Zhang, Cunren Liang, Houjie Wang, Zhenhong Li. "High Spatiotemporal Resolution River Networks Mapping on Catchment Scale Using Satellite Remote Sensing Imagery and DEM Data". Geophysical Research Letters, Vol. 51, pp. e2023GL107956, March 2024.

[13] Peng Wu, Junjie Fu, Xiaomei Yi, Guoying Wang, Lufeng Mo, Brian Tapiwanashe Maponde, Hao Liang, Chunling Tao, WenYing Ge, TengTeng Jiang, Zhen Ren. "Research on Water Extraction from High Resolution Remote Sensing Images Based on Deep Learning". Frontiers in Remote Sensing, Vol. 4, pp. 1-12, December 2023.

[14] Seetha, M., Lalitha Parameswari, D.V., Malini Devi, G. (2023). River Network Identification from Satellite Imagery Using Machine Learning Algorithms. Intelligent Computing and Communication. International Conference on Intelligent Computing and Communication 2022. Advances in Intelligent Systems and Computing, vol 1447. Springer, Singapore, Vol 1447, pp. 369-385.

[15] Srija Kanjilal, Arati Paul. "Detection of Water Bodies from Satellite Images: A Deep Learning Based Technique". 2023 3rd International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON), IEEE Xplore, Vol. 3, pp. 1-5, December 2023.

[16] Thota Balaji, V. Khanna, T. Nalini. "Deep Learning Technique For Effective Segmentation Of Water Bodies Using Remote Sensing Images". Proceedings of the 5th International Conference on Inventive Research in Computing Applications (ICIRCA 2023), IEEE Xplore, Vol. 5, pp. 157-160, 2023.

[17] Zeba Naaz, Dr. G. Malini Devi (2021). "River Network Classification from Multi-Spatial Satellite Imagery using Random Forest". Vol 10, Issue 09, pp. 707-713.

[18] Zifeng Wang, Jinbao Li, Yi Lin, Ying Meng, Junguo Liu. "GrabRiver: Graph-TheoryBased River Width Extraction from Remote Sensing Imagery". IEEE

Geoscience and Remote Sensing Letters, Vol. 19, pp. 1500505, December 2022.