

SegRivWidth: RIVER WIDTH MEASUREMENT USING DEEP LEARNING

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ABSTRACT

A precise river width measurement is crucial for various river modeling, habitat evaluation, flood risk analysis, and other hydrological environmental, and technical applications. Conventional techniques is time-consuming and error-prone, such as direct field measurements. Nowadays fast and accurate riven identification and its width measurement is highly needed to save human life during flud and other natural disaster. Recent deep learning technology can greatly be applied to identify and measure width of river automatic, fast and accurate from a remote place. The proposed deep learning based method is executed in two steps, identification of river and river width measurement. Deep learning based segmentation is used to identify river from remote sensing image. The accuracy of the semantic segmentation to identify river depends on rich spatial data and the resolution of the remote sensing images. In this work proposed SegRivWidth algorithm for automatic river width measurement from segmented images. The obtained results are compared with the ground truth river width and found better accuracy. The obtained results are also compared with the existing methods in terms of Average Absolute Error (AAE) and Root Mean Square Error (RMSE). The proposed SegRivWidth has an RMSE of 4.76 m and an AAE error of 2.16 m for the river width measurement.



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I. INTRODUCTION

Measuring river width from remote sensing images involves using satellite or aerial imagery to capture the river's spatial extent. This process typically requires first identifying the river area from the remote sensing images. This is possible with the help of the Semantic segmentation method that identifies and classifies each pixel of an image into predefined categories, such as land, water, urban areas, vegetation, and other features. Here the goal is to classify each pixel in the image into categories, such as "river" and "non-river" from satellite or aerial images. These images are captured using satellites or drones equipped with sensors such as optical, infrared, or radar.

The resolution, light conditions, cloud, and type of sensor used play an important role in determining the accuracy of the segmentation. Once the images are preprocessed to improve the quality of the image then semantic segmentation can be performed. This is typically done using deep learning methods, particularly convolutional neural networks (CNNs) or more specialized models like U-Net[1], SegNet[2], and FCN[3] which are commonly used for segmentation tasks. The River semantic segmentation accuracy depends on the varying water conditions, cloud cover, shadow, and complex river structures such as sharp curves, and multiple branches present in the images.

Many researchers proposed a different methods for the identification of the river and river width from the aerial images. An end-to-end deep learning-based U-Net neural network for segmentation of river state from drone-based images proposed by [4]. The methodology was tested on river areas in southern Poland, demonstrating its effectiveness with a Dice coefficient of 0.8524. Moreover a novel deep-learning framework for the accurate extraction of water bodies from high-resolution remote sensing imagery presented by [5]. The authors address challenges such as indistinct boundaries and shadow misclassification by leveraging the DeepLabV3+ architecture and an innovative fusion mechanism for high- and low-level features. The proposed method demonstrates superior performance, achieving an overall accuracy of 99.284%, IoU of 95.58%, precision of 97.562%, recall of 95.486%, and F1 score of 96.513%.

Since river width is one of the two basic dimensions of river extent (width and length) and one of the main components of river discharge (width, depth, and velocity). Thus, through river extent, river flow, or both, the river width is linked to it and is of great relevance among numerous applications such as environmental monitoring, flood monitoring, agriculture, water resource management, and urban planning. The aims to provide accurate and automated analysis of river conditions and the significance of river width measurements are underscored by recent developments in satellite-derived river discharge. The DeepRivWidth is a Deep learning-based semantic segmentation approach for river identification and width measurement in Synthetic Aperture Radar (SAR) images of Coastal Karnataka proposes a technique for precisely determining river widths using SAR views [6].

First, it identifies rivers and then quantifies their width using the advanced deep-learning algorithms of U-Net and DeepLabV3+. The suggested strategy outperforms current techniques in terms of accuracy, particularly in difficult weather situations. Sometimes the method fails to detect very narrow rivers and the presence of speckle noise in SAR images, which can affect the accuracy of width measurements. However super-resolution mapping (SRM) method to measure wetted river width (RWW) from remotely sensed imagery with a deep convolutional neural network (CNN) by the mixed pixel problem in coarse spatial resolution images addressed by [7]. The results were validated through experimental images taken from MODIS and Landsat data. The suggested method was not precisely measure the width of a narrow river. An innovative method based on Graph-Theory River Width Extraction from Remote Sensing Imagery presented by [8].

The proposed GrabRiver method automates the entire process from image preparation to river width calculation, utilizing graph theory to maintain river connectivity and accurately measure river widths. The method demonstrates high accuracy in experiments conducted on the Mekong and Mississippi Rivers, with results showing a strong correlation with reference measurements. The presence of clouds, cloud shadows, and snow can impact the accuracy of river width. RivWidthCloud suggested by an innovative algorithm for automating river centerlines and width calculations from optical satellite images in the presence of clouds, cloud shadows, and snow [9]. The proposed method shows high accuracy, with a root mean square error of 99 meters. Various types of river surfaces and widths measurements from satellite images such as tiny, thin, small, and large rivers proposed by [10]. The suggested method used an improved random forest algorithm combined with artificial neural networks (RF-ANN) for river surface extraction and an automated river width extraction (ARWE) method.

The error occurs for various types of extraction of 10.9%, 4.9% .1%, and 0.6% respectively. The suggested method did not accurately calculate river width when the river width is less than 10 meters. However DeepLabV3+ Convolutional Neural Network (CNN) model automatically segmented different types of river channel borders and river width using a Voronoi Diagram method presented by [11]. The model accurately classifies all four types of rivers with an accuracy of 0.97. When islands are present, the method does not accurately determine the width of the river. A novel approach of RivWidth tool used raster-based classifications from remotely sensed imagery to automatically calculate river widths [12]. In computer vision, segmentation is a subject that has been extensively researched and applied to a variety of tasks, including medical image analysis, identification of roads, buildings, ships, and other types of applications [13-17].

Moreover, the First step of river width calculation is river identification and it is formulated as a semantic segmentation problem in this work. Then traditionally many methods are available to measures width of segmeneted images such as thresholding [9], manual delineation, and NDWI-based approaches [18]. They have some restrictions because choosing the ideal threshold value is a challenge in thresholding method for river width calculation. Manual delineation is subjective and takes a lot of time. The atmospheric conditions, sensor characteristics, and water qualities can all cause mistakes in NDWI-based approaches. However, The work on semantic segmentation of rivers from aerial images is still limited. The system that combines the automatic identification of river and river width computation from remote sensing imagery is still limited.

II. METHODOLOGY

The goal of this work is to create a system that uses remote sensing images to automatically identify rivers and compute the widths of a river. The proposed approach comprises three main processing steps data augmentation, river identification using SegNet method, and River width calculation based on the centerline extraction as shown in Figure 1. River centerline extraction is done using the skeleton and distance matrix calculation method.

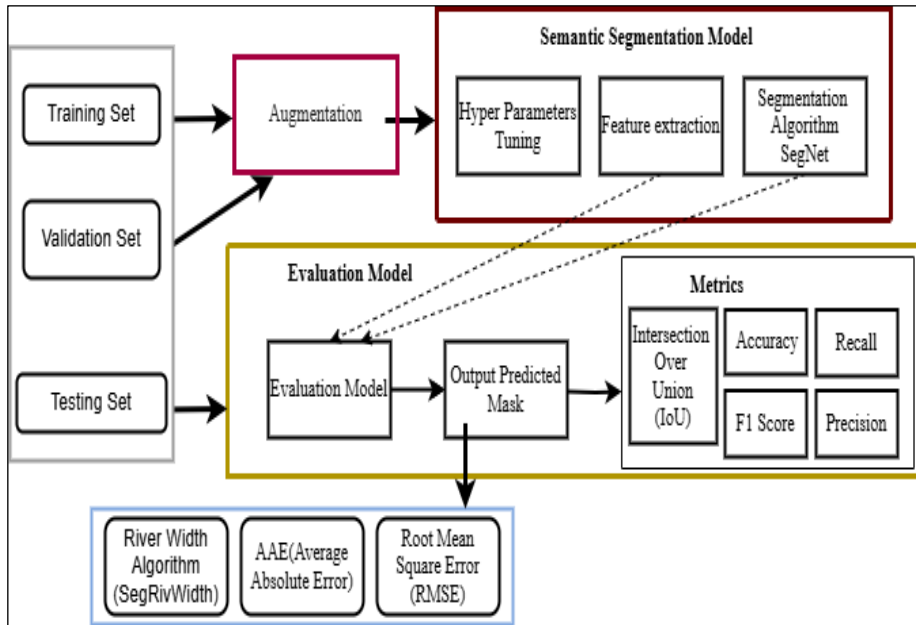


Figure 1: Block Diagram of Semantic Segmentation Model of River.
Source: Authors, (2026).

Dataset SegNet models of rivers were trained, validated, and tested using the Riwa V2 dataset [19]. These images were gathered by cellphones, drones, and unmanned aerial vehicles (UAVs). This images of rivers are different in sizes, including small, narrow, large, and tiny. Additionally, to test the trained model's performance in a variety of meteorological and seasonal settings, river photos were obtained throughout the year, including spring and rainy seasons as shown in Figure 2. A total of 1128 images in the original dataset were divided into three subsets at random: 70% of the images are used for training, 15% are used for validation, and the remaining 15% are used for testing.



Figure 2: Dataset Samples.
Source: Authors, (2026).

II.1 DATA AUGMENTATION

The original dataset is expanded by data augmentation to enhance SegNet model's accuracy and generalization for a larger dataset [20]. Generalization is the ability of a model to learn hierarchical features from data, which allows it to function effectively on a variety of tasks outside of its original training dataset. To improve the model's capacity to manage occlusion and scale fluctuations, methods such as random cropping, rotation, and scaling can be employed to intentionally increase the variety of the training data. The original images are randomly altered to achieve the augmentation [21], mostly through the use of geometric modifications such as cropping, rotations up to $\pm 45^\circ$, and flipping them horizontally and vertically.

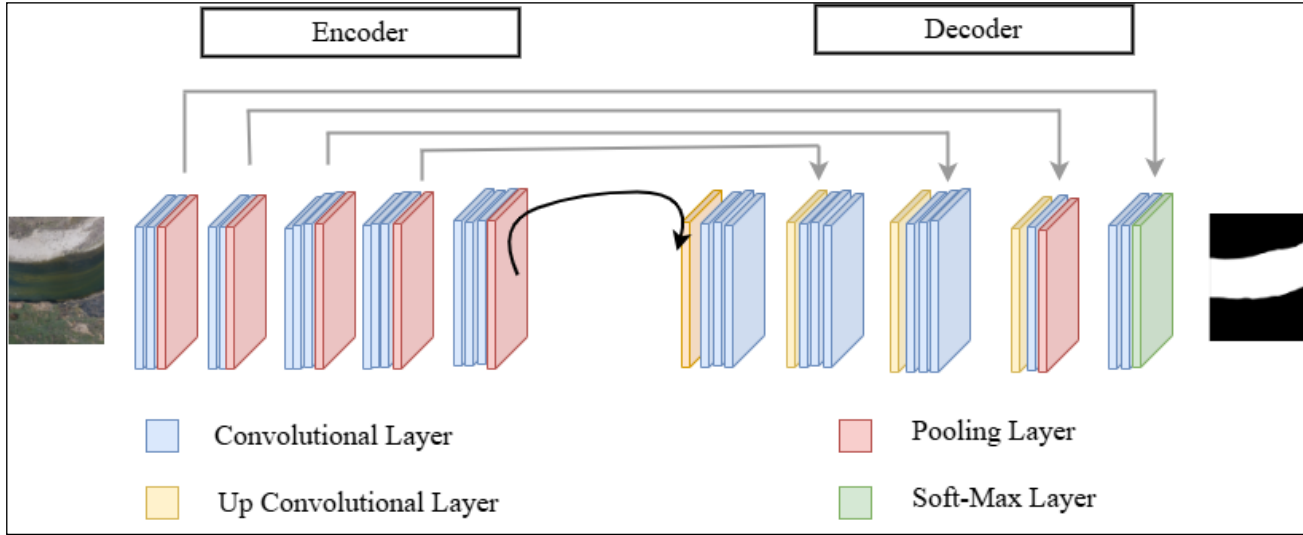


Figure 3: The Architecture of SegNet Model.
Source: Authors, (2026).

II.2 SEGNET-BASED RIVER IDENTIFICATION

Semantic segmentation is used to identify rivers from remote sensing imagery. It is a process to partition the images which have similar types of characteristics. This work uses a SegNet architecture for semantic segmentation as shown in Figure 3. SegNet is a specialized deep learning architecture that uses an encoder-decoder structure made up of CNNs and pooling layers to identify image pixels. It is created especially for semantic segmentation applications. The encoder component of SegNet consists of several convolutional layers followed by pooling layers that collect high-level characteristics from the input image.

It down-samples the image and it reduce spatial dimension. On the other hand, the decoder part generates pixel-wise segmentation masks and refines feature representations by up-sampling rather than down-sampling, while maintaining the structure of the encoder. Skip connections across relevant layers help to preserve spatial information lost during encoder down-sampling, improving segmentation accuracy. The final segmented image is obtained by applying a softmax layer to every pixel in the output feature map. This process assigns a probability distribution across a binary class of river and background. An encoder and a decoder, each with 13 convolutional layers, make up the SegNet framework as shown in Figure 3

The encoder layers first make use of a 64x64 convolution layer with a small receptive field. They include both BN (Batch Normalization) operations and ReLU activation functions. Similarly, the 128x128 convolution layer appears on two levels, the 256x256 convolution layer appears on three layers, the 512x512 convolution layer appears on three layers, and the 512x512 convolution layer appears on three layers. To preserve the feature maps' spatial dimensions, max pooling operations are carried out after each convolutional layer. A 3x3 kernel size filter with the same padding is used at the encoder side in conjunction with convolution, while a 2x2 kernel size filter with stride = 2 is used at the decoder side.

II.3 RIVER WIDTH MEASUREMENT ALGORITHM

Algorithm 1: River Width Calculation

Input: Predicted Output of test dataset \hat{G}_{test}
Output: Average River width mw^{model}

```

1  for each sample of test set do
2       $\hat{G}_{gray} = f(col2gray(\hat{G}_{test}))$  /* convert color image to grayscale image */
3       $\hat{G}_{thresh} = f(gray2thresh(\hat{G}_{gray}))$  /* convert into threshold image */
4       $dist = copy(\hat{G}_{thresh})$  /* threshold image copied into distance */
5       $dist_{trans} = DT(dist, euclidean_{dist})$  /* applied distance transform on the threshold image */
6       $skele_{ton} = skeleton(copy(\hat{G}_{thresh}), medial_{axis})$  /* to get skeleton medial axis)
7       $centerline_{dist} = dist_{trans} * skele_{ton}$  /* to get centerline distance */
8
9  end for
10 for  $skele_{ton} \neq 0$  do
11      $avg = mean(centerline_{dist})$ 
12 end for
13  $mw^{model} = 2 * avg$  /* average River width */

```

Source: Authors, (2026).

The river width calculation algorithm SegRivWidth is given in Algorithm 1. The width of the river is calculated using the binary segmentation map made up of the river pixels in the foreground class \hat{G}_{test} . River width is defined as the distance between two locations on the riverbank that is orthogonal to the river's centerline. The two-step method to calculate river width is River centerline calculation and measurement of the distance between two locations on the riverbank that are orthogonal to the river centerline.

DT (Distance Transform) is applied on the thresholded river grayscale image. Then the medial axis of the extracted river is calculated using the `skele_ton`. This skeleton is then taken to represent the river's centerline using $centerline_{dist}$. Let's use $RPI, i = 1, 2, \dots, N$ to represent the N pixels on the river centerline. The closest point $RPj (Pj \in Pi)$ on the river centerline is initially identified given a point on the river bank Q . Using the formula of river width calculation is

$$mW^{model} = \sigma (2 Dist(Q, RP)) \tag{1}$$

Where $DIST (RP, Q)$ is the Euclidean distance between locations P and Q . This width mW , which is in the unit of pixels, can be multiplied by a scaling factor σ to convert it to the metric unit (meters).

II.4 PERFORMANCE MATRICES

Different performance metrics are used for river identification and river width calculation as described in the following section.

II.4.1 River Identification Metrics

Performance metrics like accuracy, precision, recall, IOU, and F1 score are commonly used to assess the effectiveness of semantic segmentation. The test dataset's confusion matrix served as the base for calculating the various evolution metrics. They described themselves as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{2}$$

$$Recall = \frac{TP}{TP + FN}, \tag{3}$$

$$Precision = \frac{TP}{TP + FP}, \tag{4}$$

$$F1score = 2 \times \frac{precision \times recall}{precision + recall} \tag{5}$$

$$IOU = \frac{TP}{TP + FP + FN}, \tag{6}$$

False Positive (FP) indicates the number of river pixels that are incorrectly classified, False Negative (FN) indicates the number of background pixels other than river pixels that are incorrectly classified, True Positive (TP) indicates the number of river pixels that are correctly classified, and True Negative (TN) indicates the number of background pixels other than river pixels that are correctly classified. The model's overall performance across all classes is shown by accuracy. A recall is calculated by dividing the number of correctly identified positive samples by the total number of positive samples in the test set. The precision of an image is defined as the proportion of accurately predicted positive samples among all expected positive samples. The F1 score is a representation of the precision and recall harmonic average values. The Predicted and original image overlap ratio is represented by the IOU.

II.4.2 River Width Metrics:

The effectiveness of the proposed method for river width calculation mw^{model} is compared with the river width of the ground truth images mw_g . The Average Absolute Error (AAE) and Root Mean Square Error (RMSE) are used to measure the performance of the method. They are defined as under:

$$Average\ Absolute\ Error = \frac{absolute(mw_g - mw^{model})}{N} \tag{7}$$

$$Root\ Mean\ Square\ Error = \sqrt{\frac{\sum(mw_g - mw^{model})^2}{N}} \tag{8}$$

Where N is the total number of locations considered for river width measurement

III RESULT AND DISCUSSION

III.1 RIVER IDENTIFICATION TRAINING PHASE

The River Identification Training Phase used two semantic segmentation algorithms, FCN and SegNet, trained on the RIWA V2 dataset. This dataset is divided into three parts: test, validation, and training. The SegNet and FCN are trained independently on the same dataset using identical training, validation, and test split. The model is trained and evaluated on Google Colab with an NVIDIA T4 Tesla GPU, 12 GB of RAM, CUDA version 12.2, and an Intel Xeon CPU running at 2.00 GHz. The deep learning library PyTorch is used to train the model. The Learning Rate ϵ of the model is initialized by the 1×10^{-2} , Batch Size β of 4, Hidden Layers of 64, and image size of 512×512 pixels. The proposed model used a Binary Cross Entropy (BCE) loss model. It used Adam optimizer for FCN and SegNet to optimize the weight parameters of the model.

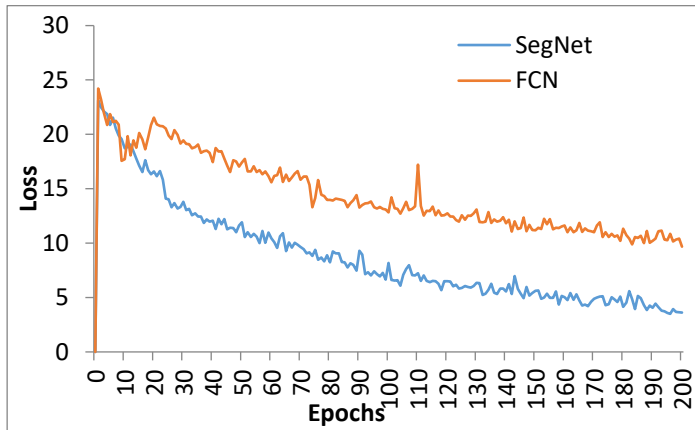


Figure 4: Loss curve during Training Phase.
Source: Authors, (2026).

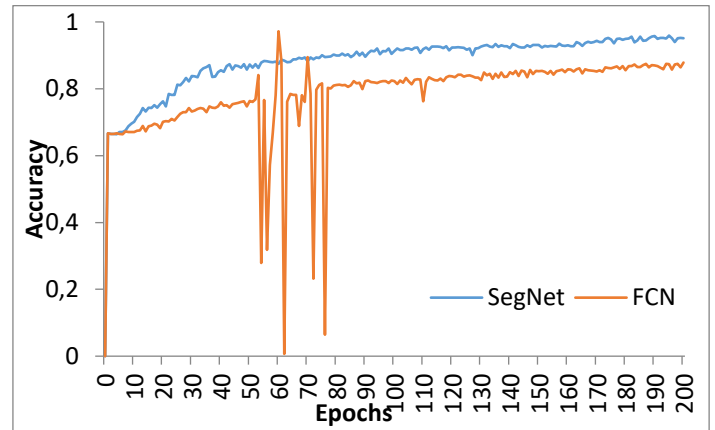


Figure 5: Accuracy Curve during the Training Phase.
Source: Authors, (2026).

During the training phase of the model (FCN and SegNet) the Loss, Accuracy, IoU score, and Training Time are calculated. Both of the models are trained for 200 epochs and the graph of epochs vs loss and epochs vs accuracy is shown in Figure 4 and Figure 5 respectively. Result shows SegNet model performed better than the FCN model. The Training time required for the FCN is approximately 6 hrs whereas the training time for the SegNet is approximately 6 hrs and 25 min. Moreover to measure the effectiveness of the model IOU score is also measured for the validation and training phase of the FCN and SegNet model as shown in Table 1. Both algorithms demonstrate competitive performance, with FCN achieving an IoU score of 78.25% and SegNet achieving an IoU score of 89.55% during the validation phase. Both method FCN and SegNet methods segmented images accurately but compared to FCN, SegNet produces a more accurate river segmentation as shown in Figure 6.

Table 1: Training Phase Evaluation Parameters.

Model Name	IoU score (Training Phase) (%)	IoU score (Validation Phase) (%)	Training Time
FCN	89.55	78.25	5 hrs and 55 min
SegNet	92.48	88.67	6 hrs and 25 min

Source: Authors, (2026).

III.2 RIVER IDENTIFICATION TESTING PHASE

Table 2. Testing Phase Evaluation Parameters.

Model Name	Precision (%)	Recall (%)	F1 score (%)
FCN	78.89	77.92	78.40
SegNet	85.56	89.23	87.35

Source: Authors, (2026).

The semantic segmentation of rivers from Aerial images is challenging due to the presence of multiple water bodies, shadows, and backgrounds with similar kinds of features. The performance precision, recall, and F1 score of FCN and SegNet algorithms are compared with ground truth values. It can be seen that both the algorithms perform well and achieve good competent results as shown in Table 2. The SegNet achieves the recall value of 89.23% however the FCN achieves 77.92% of recall value. Further F1 score of FCN is 78.40% while 87.35 for the SegNet Method. However, it was observed SegNet method is more accurate than the FCN method for semantic segmentation of the river as shown in Figure 6.

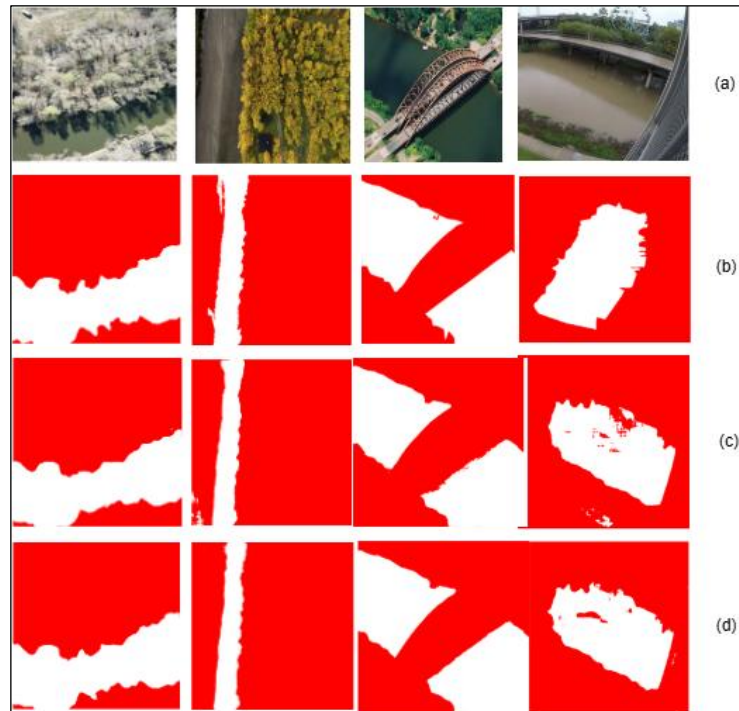


Figure 6: (a)Original Image (b) Ground Truth (c) Sementic Segmented Output Images using FCN (d)River Semantic Segmentation Output Images using SegNet Method.
Source: Authors, (2026).

III.3 RIVER WIDTH RESULTS

Table 3: River width results.

Test Image	Actual Width mw_g (meter)	mw^{FCN} (meter)	mw^{SegNet} (meter)
1	37.76	39.2	36.44
2	18.22	15.85	17.27
3	45.98	48.71	47.78
4	30.67	20.97	25.7

Source: Authors, (2026).

A comparison was made between the estimated and actual river widths. Actual river width is determined by ground truth images. The measured width at a few locations using the segmentation findings from SegNet and FCN is displayed in Table 3. Both the method FCN and SegNet are used to calculate the width of the river from the river segmented output images. The estimated width is not same actual river width as segmentations boundary errors. As Segmentation boundary errors results due to inaccurate object boundaries during image segmentation method which leads further error for river width calculation. Segmentation boundary error depends on algorithm such as edge based, region based or deep learning based algorithm that misclassify river segment. The segmented river images further analysed for the river width measurement that compounded the initial error segmentation and river width measurement algorithm error. It means if the boundary is narrower than the actual object then width will be underestimated.

Using the segmentation findings of FCN, the average absolute measurement error was 4.06 m, whereas using the segmentation results of SegNet, it was 2.16 m. Additionally, using the FCN segmentation map, the root mean square error (RMSE) was 5.22 m while using the SegNet segmentation map, it was 4.76 m. The more precise segmentation map produced by SegNet is the primary reason the estimated river width using SegNet segmentation method is more accurate than the FCN method. This finding is the significance of precisely identifying rivers and calculation of river width. The suggested method for measuring river width performs noticeably better than the previously published research as shown in Table 4.

Table 4. Comparative analysis with published work.

Algorithm	AAE Error (m)	RMS Error(m)
RivWidthCloud (9)	43.1	99.2
DeepRivWidth (6)	20.05	24.9
RWW (2)	-	14.41
GrabRiver(8)	26.05	47.3
Proposed: SegRivWidth	2.16	4.76

Source: Authors, (2026).

IV. CONCLUSION

Using Deep learning can be done river segmentation and width measurement fast and automatic from remote place to save human life during natural disasters. The suggested method first identifies the river images from the aerial images using semantic segmentation and then calculates the width of the river. The use of CNN-based encoder-decoder type architecture eliminates the requirement of human intervention for adjusting the threshold value and seed point of the input image. Both the FCN and SegNet model's evaluation parameters were compared during the training, and testing phase. The result shows that the SegNet Model accurately classifies the image pixel of rivers from the input images. Moreover, the visual result also conveyed that SegNet is superior to the FCN method for river semantic segmentation. The SegRivWidth measures the width of the river from the segmented result and would be used for the better management and planning of water resources.

The input to the SegRivWidth algorithm is a Semantic Segmented image that is used to calculate the river width and compare it with the original ground truth width measurement. However, the accuracy of the river width measurement depends on how the river image is identified properly from the aerial images. The AAE and RMS error is calculated for the SegNet model and compared with the other five methods reported recently in the literature. The river width calculation for the SegNet model had an AAE error was 2.16 m and an RMS error was 4.76 m. These findings of the river width performed better than the methods currently used for extracting river width. This method would be used for automatic calculation of river width, flood monitoring, agriculture, water resource management, and urban planning.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Dr. Miral Jerambhai Patel and Dr. Hasmukh P Koringa.

Methodology: Dr. Miral Jerambhai Patel and Dr. Hasmukh P Koringa.

Investigation: Dr. Miral Jerambhai Patel and Dr. Hasmukh P Koringa.

Discussion of results: Dr. Miral Jerambhai Patel, Dr. Bhavik D. Upadhyay and Dr. Ashish K Sarvaiya.

Writing – Original Draft: Dr. Miral Jerambhai Patel, Dr. Hasmukh P Koringa and Ms. Sonal T. Dave

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Resources: Dr. Ashish K Sarvaiya and Priyank K.Shah

Supervision: Dr. Bhavik D. Upadhyay, Ms. Sonal T. Dave and Priyank K.Shah.

Approval of the final text: Dr. Miral Jerambhai Patel, Ms. Sonal T. Dave and Dr. Ashish K Sarvaiya.

VI. ABBREVIATIONS

AAE: Average Absolute Error, RMSE: Root Mean Square Error, CNN: Convolutional Neural Networks, SAR: Synthetic Aperture Radar, SRM: Super-Resolution Mapping, RWW: River Wetted Width, RF-ANN: Random Forest algorithm combined with Artificial Neural Networks, ARWE: Automated River Width Extraction, UAV: Unmanned Aerial Vehicles, BN: Batch Normalization, DT: Distance Transform, FP: False Positive, FN:False Negative, TP:Positive , TN: True Negative, AAE: Average Absolute Error, NDWI :Normalized difference water index

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