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Enhanced Flood Detection Through Precise Water Segmentation Using Advanced Deep Learning Models

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ABSTRACT

Floods are natural disasters that can result in significant social, economic, and environmental impacts. Timely and accurate flood detection is crucial for effective disaster management and mitigation. This paper addresses the importance of water segmentation in flood detection and water engineering applications, emphasizing the need for precise delineation of water areas in flood-hit regions. Accurate water segmentation not only aids in assessing the extent of flooding but also plays a vital role in predicting and preventing potential flood events. This study explores the application of advanced deep learning models, namely SegNet, UNet, and FCN32 for automated flood area segmentation. Leveraging a dataset comprising 290 images depicting flood-affected areas, the models are trained to accurately delineate water regions within the images. The experiment results demonstrate the efficacy of these models in effectively segmenting floodwaters. Among the tested models, SegNet emerges as the top performer, achieving an impressive precision rate of 88%. This superior performance underscores the potential of deep learning techniques in enhancing flood detection and response capabilities, paving the way for more efficient and reliable flood prediction systems.

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1. Introduction

Floods, which occur when water overflows onto normally dry land, have various causes such as excessive rainwater in saturated ground, overflowing water bodies, rapid snow or ice melting, storm surges, and tsunamis. Climate change exacerbates these events, leading to more intense precipitation and temperature variations. Poor water management practices, including dam discharges and neglected bank maintenance, can also contribute to flooding. Most floods result from extreme rainfall, allowing for some predictability. However, flash floods, developing rapidly within hours, are highly unpredictable and dangerous. Climate change's influence on extreme weather events, such as hurricanes and sea-level rise, poses an increasing threat. Floods cause significant damage globally, exceeding $40 billion annually, with thousands of fatalities. Novel approaches using Artificial Intelligence algorithms for automated image and video analysis from various sources, including surveillance cameras, drones, and social media, are crucial for effective flood monitoring and early warnings [1-4].

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Floods, devastating natural disasters affecting societies globally, have intensified due to climate change, urbanization, and deforestation. Detecting floods early is crucial for minimizing their impact, prompting a shift from traditional methods to advanced technologies like deep learning models. Accurate delineation of water bodies through water segmentation, classifying pixels in images, is essential for precise flood detection. Leveraging deep learning models, particularly for water segmentation, aims to surpass the limitations of traditional techniques in terms of accuracy, speed, and scalability. The growing severity of floods underscores the need for innovative tools to reduce their impact, emphasizing the importance of automated image and video analysis using Artificial Intelligence algorithms for comprehensive flood monitoring and early detection [4-7].

Existing flood detection methods, relying on remote sensing technologies and machine learning algorithms, have shown promise but are hindered by challenges such as false positives, limited scalability, and the inability to capture subtle changes in water dynamics. The introduction of advanced deep learning models offers a potential breakthrough, leveraging the power of neural networks to discern intricate patterns and variations in satellite imagery. Recently, a discernible pattern has arisen, marked by the increasing adoption of deep learning for image analysis. These applications extend across diverse domains, encompassing image analysis such as recognition, classification, and segmentation. Deep neural networks, functioning as comprehensive end-to-end learning models, showcase their ability to autonomously extract intricate features from any high dimensional images. Particularly noteworthy is the application of deep learning algorithms in water detection and segmentation. The adoption of advanced deep learning models is motivated by their capacity to learn hierarchical features and representations from complex data. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their variants have demonstrated success in image classification and segmentation tasks, making them well-suited for the nuanced demands of flood detection through precise water segmentation.

The main goal of this study is to propel the capabilities of flood detection by employing cutting-edge deep learning models in conjunction with precise water segmentation. Through this approach, we seek to surmount the constraints inherent in existing methods, offering a more precise and timely methodology for the identification and monitoring of flood events. Within this manuscript, we embark on an extensive exploration of water segmentation, leveraging the formidable capabilities of contemporary deep learning models. Our toolkit encompasses well-established models such as SegNet [8], UNet [9], and FCN32 [10], each distinguished by intricate architectures and a profound understanding of visual patterns. These models contribute a wealth of expertise to the domain of water segmentation. We applied this methodology to a publicly available water segmentation dataset, conducting a comprehensive comparative analysis of state-of-the-art deep learning models across 290 images.

Section 2 provides an overview of related studies and previous implementations of deep-learning models in the realm of water segmentation. Moving on to Section 3, we detail our methodology, including information about the dataset and an introduction to three deep-learning models. Finally, in Section 4, we present the experimental results and conduct a statistical analysis of the performance of these deep learning models.

2. Related works

In recent times, there has been a surge in the application of machine learning and deep learning models for tasks within computer vision, notably in object detection and segmentation [11-12]. The prominence of these models in the field of image processing, specifically for flood label detection, has grown considerably. The literature, however, remains relatively sparse on this particular subject.

Yang et al. [13] took on the task of water level monitoring by employing a visual recognition method. A river camera was utilized to measure flood depth resulting from rising water levels. The incorporation of techniques such as the Laplacian method [14] and probabilistic Hough transform [15] allowed for the detection of edges in various objects and the computation of the waterline's straightness. In a separate study, [16] conducted remote calculations of flood levels by measuring the length of a ruler in footage, employing Convolutional Neural Networks (CNNs). Their findings demonstrated the superior performance of CNNs over traditional image processing algorithms, showcasing a standard deviation of 6.69 mm.

In the work [17], CNNs were applied to sift through flooding photos on social media platforms, facilitating label detection. More recently, [18] undertook the estimation of flood depth by identifying submerged vehicles in flooded photos, utilizing the Mask R–CNN framework [19]. The calculated flood depth was then compared with 3D rendered objects using feature maps extracted by Visual Geometry Group Nets [20]. This proposed methodology demonstrated impressive accuracy, with absolute error values reaching as low as 6.49 cm in flood depth calculation. In [21], the authors delved into the study of flood depth using image processing and deep learning, employing traffic stop signs as ubiquitous measurement benchmarks in flood photos. Their approach estimated flood depth in crowdsourced photos with a mean absolute error of 12 inches. Collectively, these studies contribute to the evolving landscape of flood label detection, showcasing the versatility of approaches ranging from visual recognition and traditional image processing to the application of advanced deep learning models. In [4], the WSOC dataset was introduced. This dataset, an augmentation of existing publicly available datasets, includes diverse water-related labels (e.g., river, sea, waves).

Various state-of-the-art Deep Learning models for semantic segmentation were explored in this study, combining different backbones commonly used for image labeling with semantic segmentation models. Additionally, a new Python package named "FloodImageClassifier" was developed [22]. This package is designed for the classification and detection of objects within collected flood images. "FloodImageClassifier" incorporates various CNN architectures, including YOLOv3, Fast R–CNN (Region-based CNN), Mask R–CNN, SSD MobileNet (Single Shot MultiBox Detector), and EfficientDet, enabling simultaneous object detection and segmentation. The package also includes concepts such as Canny Edge Detection and aspect ratio for floodwater level estimation.

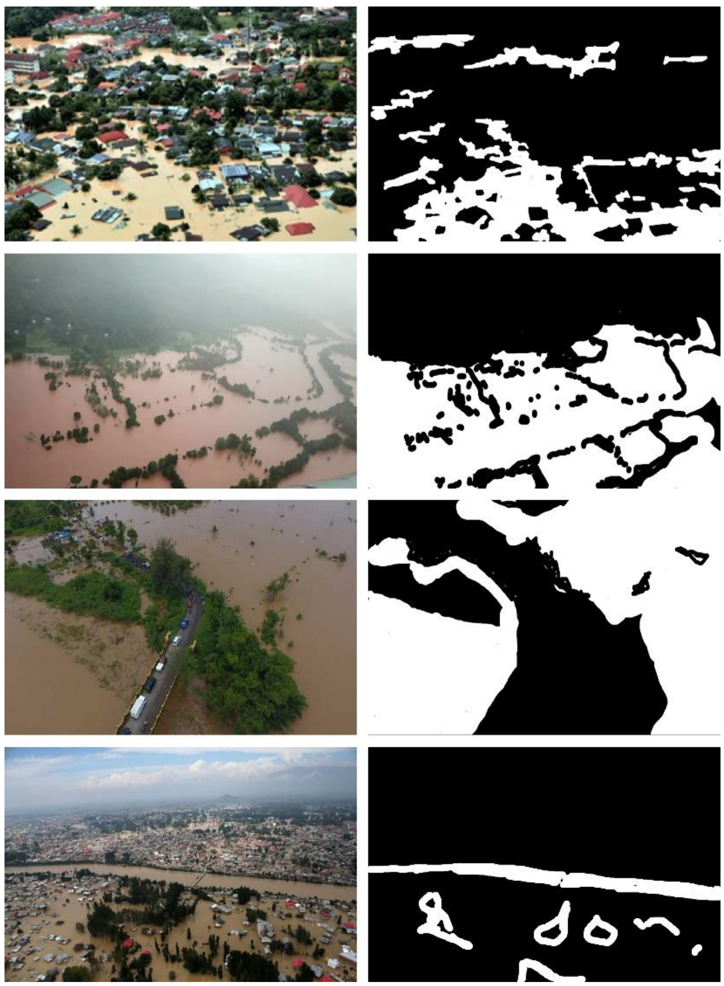

Fig. 1. Some examples with mask image [24]

3. Methods

3.1. Dataset

The flood area segmentation dataset provides a comprehensive collection of 290 images capturing regions affected by flooding, each paired with self-annotated mask images that precisely outline the areas submerged in water [23]. These masks were meticulously generated using Label Studio, a versatile and open-source data labeling software known for its accuracy and efficiency in annotation tasks.

The primary objective of this dataset is to facilitate the development and training of robust segmentation models.

These models aim to precisely delineate the water-affected regions within photographs depicting areas impacted by floods. The annotations within the dataset serve as a valuable resource for enhancing the accuracy and efficacy of segmentation algorithms, enabling the creation of model’s adept at recognizing and isolating flood-induced water regions in a given image.

3.2. Deep learning models

In our quest for achieving the accurate and efficient segmentation of floodwater, we harnessed the remarkable capabilities of three distinguished deep learning models. Each of these models boasts unique strengths and intricate architectural features, making them pivotal contributors to the landscape of image analysis and segmentation. The trio of SegNet, UNet, and FCN32 stand out as foundational pillars in this domain, having demonstrated their prowess in handling complex segmentation tasks with precision and effectiveness. These models serve as integral components in our research, offering a diverse set of tools to explore and optimize the segmentation of floodwater, contributing to advancements in the broader field of computer vision and image analysis.

SegNet, a pioneering deep learning architecture designed for semantic image segmentation, boasts a sophisticated structure that has significantly influenced the landscape of computer vision tasks.

Developed by the Visual Geometry Group at the University of Oxford, SegNet's architecture is meticulously crafted to balance computational efficiency with high-performance segmentation capabilities. At its core, SegNet follows an encoder-decoder framework, where the encoder progressively reduces spatial dimensions while capturing essential features from input images. This is achieved through a series of convolutional and pooling layers, with the pooling indices being stored during the encoding process. The critical innovation of SegNet lies in its decoder, which employs upsampling techniques based on the stored pooling indices. This enables precise reconstruction of segmented output, recovering intricate details crucial for accurate segmentation. The encoder-decoder structure is further enriched by incorporating skip connections, allowing the network to capture both local and global context information. SegNet's architecture is characterized by its lightweight design, making it computationally efficient and suitable for real-time applications. Delving into the details, the encoder module typically consists of convolutional layers with batch normalization and rectified linear unit (ReLU) activation functions, facilitating feature extraction. Pooling layers, specifically max-pooling, are strategically placed to reduce spatial dimensions while retaining essential information. The decoder module employs upsampling layers, guided by the stored indices, to reconstruct the segmented output. Skip connections, established between corresponding layers in the encoder and decoder, enhance the network's ability to capture hierarchical features. SegNet's adaptability and effectiveness extend beyond its architecture, making it particularly well-suited for a diverse range of applications.

Its implementation in tasks such as autonomous vehicles, medical image analysis, and, in our specific context, floodwater segmentation, underscores its versatility and the impact of its nuanced design on the advancement of semantic segmentation techniques. UNet, a groundbreaking convolutional neural network (CNN) architecture, has emerged as a cornerstone in the realm of biomedical image segmentation, showcasing exceptional performance in various computer vision tasks. Introduced by Ronneberger et al. in 2015, UNet was specifically designed to address challenges related to object localization and semantic segmentation. The architecture of UNet follows a U-shaped design, featuring a contracting path, a bottleneck, and an expansive path. The contracting path, consisting of multiple convolutional and max-pooling layers, captures hierarchical features while gradually reducing spatial dimensions. The bottleneck, at the center of the U, serves as a bridge between the contracting and expansive paths, preserving critical contextual information. The expansive path, characterized by up-convolutional layers, facilitates precise localization and segmentation by gradually restoring spatial dimensions. Notably, skip connections are incorporated, linking corresponding layers in the contracting and expansive paths. This innovation allows UNet to recover fine-grained details, enhancing its capacity to delineate complex structures in images. UNet's architecture is celebrated for its ability to handle limited annotated data efficiently, making it a favored choice in medical imaging applications, where labeled datasets are often scarce. The adaptability and effectiveness of UNet in diverse segmentation tasks underscore its impact on advancing the field of computer vision.

FCN32, or Fully Convolutional Network with a stride of 32 pixels, represents a pivotal advancement in semantic segmentation by eliminating the need for fully connected layers, enabling efficient end-to-end pixel-wise predictions. Introduced by Shelhamer et al., FCN32 is renowned for its ability to process input images of arbitrary sizes and produce dense pixel-level predictions. The architecture is characterized by a sequence of convolutional layers with large receptive fields, efficiently capturing global context information. Importantly, FCN32 incorporates skip connections, linking convolutional layers with corresponding layers in the decoding path to enhance the localization precision of the model. The decoding process involves up-sampling layers, allowing the network

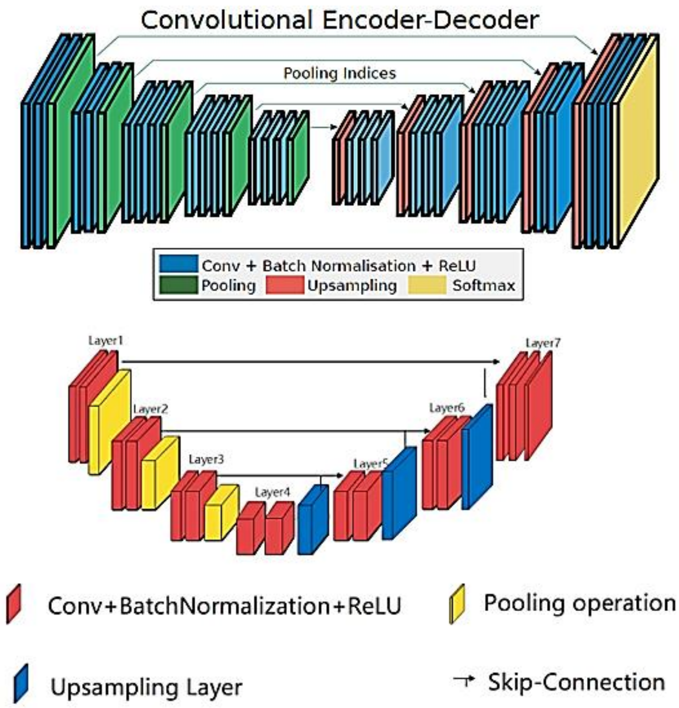

Fig. 2. Top: The Architecture of SegNet. Down: UNet

to produce pixel-wise predictions while preserving spatial information. This approach enables FCN32 to effectively handle varying input sizes and maintain detailed segmentation results. The absence of fully connected layers contributes to computational efficiency and faster inference times, making FCN32 a preferred choice in applications where real-time processing is crucial, such as in our pursuit of floodwater segmentation. The adaptability and accuracy of FCN32 underscore its significance in advancing the field of semantic segmentation and image understanding.

4. Experiments

4.1. Parameter setting

The development of the deep learning model, as detailed in this investigation, was conducted using Keras. All experiments were carried out on a 8-core PC with an i7-6700 processor running at 3.4GHz, 128GB of RAM, and an NVIDIA GeForce RTX 3090. Our approach involved setting the margin at 0.2, implementing random sampling, and executing 1000 training epochs. We employed a publicly accessible dataset consisting of jpeg images for water segmentation. Our preprocessing steps included normalization and standardization of the dimensions for all images. In the course of this study, we allocated 75% of these images for training and validation, reserving the remaining 25% for the testing dataset.

4.2. Metrics

Performance metrics play a crucial role in evaluating the effectiveness of segmentation models. Precision, Sensitivity, also known as True Positive Rate or Recall, and the Dice Coefficient are three crucial metrics in the evaluation of segmentation models. The precision metric provides insights into the model's ability to make accurate positive predictions, minimizing the occurrence of false positives. Sensitivity is formulated as the ratio of true positive predictions to the total number of actual positive instances. It gauges the ability of a segmentation model to accurately capture all relevant regions within the ground truth, emphasizing the minimization of false negatives. On the other hand, the Dice Coefficient measures the similarity between the predicted and true segmentations by evaluating the overlap between the two. A higher Dice Coefficient indicates better agreement between the predicted and actual segmentations, emphasizing a balanced consideration of false positives and false negatives. Sensitivity and Dice Coefficient, together, offer a comprehensive understanding of a segmentation model's performance by highlighting its ability to capture relevant regions while maintaining a precise delineation of the segmented areas. These metrics are particularly valuable in medical imaging and other fields where the accurate identification of specific regions is crucial.

$$Dice = \frac{2 \times TP}{2 \times TP + FP + FN} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

4.3. Results

Tables 1 and 2 provide a comprehensive examination of our analysis, systematically evaluating the performance of different models in water segmentation across a diverse range of metrics. In Table 1, we showcase the results obtained by employing deep learning models with VGG19 [20] as the backbone on the flood area segmentation dataset. On the other hand, Table 2 delves into a detailed exploration of the efficacy of our models utilizing ResNet50 [24]. The VGG-19 is characterized by a configuration comprising 19 layers, including 16 convolutional layers and three fully connected layers. These layers employ 3x3 filters with a stride and padding size of 1 pixel. The choice of compact kernel sizes serves to limit the number of parameters while ensuring comprehensive image coverage. In the VGG-19 model, a 2x2 max pooling operation with a stride of 2 is performed. This model achieved second place in classification and first place in positioning at the 2014 ILSVRC competition, boasting a total of 138 million parameters. ResNet50, belonging to the ResNet (Residual Network) family, stands out as a potent deep-learning model known for its architectural depth and structural innovation. Consisting of a total of 50 layers, the model's architecture introduces groundbreaking residual blocks that redefine the landscape of deep neural networks. These blocks incorporate skip connections, allowing the model to train with exceptional depth while mitigating the vanishing gradient problem. This profound structural innovation empowers ResNet50 to adeptly capture intricate image features, even in the presence of complex and noisy data. Essentially, the architecture's depth accommodates increasingly complex visual data, facilitating the extraction of fine-grained image details.

With 60.8 million parameters, this network excels at recognizing nuanced image variations, making it invaluable for tasks such as medical image detection and classification. The model's distinctive structural resilience and depth position it as a top choice for addressing intricate challenges in image analysis and classification.

Table 1 presents a segmentation comparison of various models with VGG19 as the backbone. The performance metrics, including Dice coefficient, sensitivity, and precision, showcase the effectiveness of each model in accurately delineating water regions in the flood area segmentation dataset. FCN32 demonstrates a Dice coefficient of 0.671±0.0027, sensitivity of 0.652±0.0038, and precision of 0.74±0.028. U-Net exhibits a higher Dice coefficient of 0.75±0.0027, sensitivity of 0.71±0.0019, and precision of 0.821±0.0010. SegNet outperforms both with a Dice coefficient of 0.810±0.0026, sensitivity of 0.77±0.0070, and precision of 0.85±0.054. These results provide a detailed insight into the segmentation capabilities of each model, aiding in the evaluation and selection of the most suitable approach for water segmentation tasks. Table 2 presents a segmentation comparison of various models, employing ResNet50 as the backbone. The table showcases key performance metrics, including Dice coefficient, sensitivity, and precision, offering insights into the models' efficacy in accurately segmenting water regions within the flood area dataset. FCN32 demonstrates a Dice coefficient of 0.690±0.0025, sensitivity of 0.68±0.0024, and precision of 0.77±0.033. U-Net exhibits superior performance with a Dice coefficient of 0.79±0.0038, sensitivity of 0.73±0.0027, and precision of 0.850±0.0034. SegNet continues to excel with a Dice coefficient of 0.84±0.0042, sensitivity of 0.80±0.0062, and precision of 0.88±0.039. These comprehensive metrics aid in the evaluation and comparison of the models, guiding the selection of the most suitable approach for effective water segmentation tasks using ResNet50 as the underlying architecture.

4.4. Statistical analysis

To assess potential statistically significant differences in segmentation performance metrics (Precision, Recall, and Dice) among the models, we can employ statistical techniques like Analysis of Variance (ANOVA), designed for simultaneous comparison of multiple groups. ANOVA allows exploration into whether meaningful disparities exist within the means of different models. The p-values derived from ANOVA serve as indicators to ascertain if significant variations exist among the models for each metric. If the p-values fall below a predetermined significance threshold (e.g., 0.05), it leads to the conclusion that indeed significant differences exist among the models.

The outcomes of the analysis of variance (ANOVA) reveal noteworthy p-values, indicating substantial differences among the models across all three metrics: Precision, Recall, and Dice. Specifically, the p-value for Precision is 3.9e-03, signifying a significant divergence in accuracy among the models. Similarly, the Recall metric yields a p-value of 4.4e-03, reaffirming a significant difference in precision across the models. Additionally, the Dice metric exhibits a small p-value of 5.4e-04, emphasizing a notable variance in recall among the models. In summary, the statistical analysis underscores

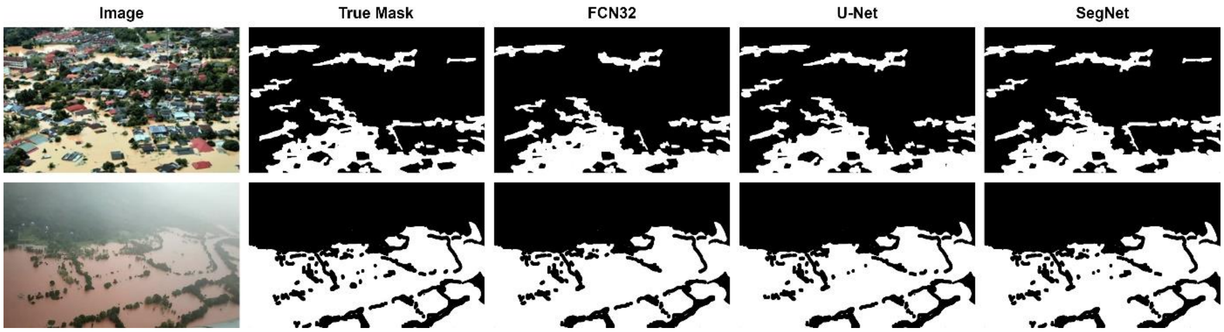

Fig. 3. Segmentation results of FCN, U-Net, and SegNet

Table 1

Segmentation comparison of the different models: VGG19 as backbone

Model	**Dice**	**Sensitivity**	**Precision**
FCN32	0.671±0.0027	0.652±0.0038	0.74±0.028
U-Net	0.75±0.0027	0.71±0.0019	0.821±0.0010
SegNet	0.810±0.0026	0.77±0.0070	0.85±0.054

Table 2

Segmentation comparison of the different models: ResNet50 as backbone

Model	**Dice**	**Sensitivity**	**Precision**
FCN32	0.690±0.0025	0.68±0.0024	0.77±0.033
U-Net	0.79±0.0038	0.73±0.0027	0.850±0.0034
SegNet	0.84±0.0042	0.80±0.0062	0.88±0.039
Model	Dice	Sensitivity	Precision
FCN32	0.671±0.0027	0.652±0.0038	0.74±0.028
U-Net	0.75±0.0027	0.71±0.0019	0.821±0.0010
SegNet	0.810±0.0026	0.77±0.0070	0.85±0.054

significant performance disparities among segmentation models across all metrics, underscoring the influential role of model selection in shaping classification performance.

5. Conclusion

In this study, deep-learning models explicitly designed for floodwater segmentation were thoroughly evaluated. Prominent deep learning architectures were employed, and their performance was meticulously assessed using diverse metrics, including Precision, Recall, and Dice. Valuable insights into the efficacy of these models in addressing the challenge of water segmentation were provided through our comprehensive analysis. SegNet emerged as the top performer, showcasing outstanding and consistent results across all metrics, highlighting its efficiency and effectiveness in accurately segmenting water. With a Dice coefficient of 0.84 and a precision of 0.88, SegNet excelled in minimizing false positives, a critical aspect of this application. Furthermore, a flawless recall score of 0.80 was achieved, demonstrating SegNet's ability to accurately capture the majority of genuine water patches.

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