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Identification of Irrigation Canals Using Deep Learning Techniques from Remote Sensing Data

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ABSTRACT

Objective: Water scarcity is a critical global concern, particularly in arid regions such as Iran, where agriculture uses a substantial portion of the available water. Accurate and up-to-date mapping of irrigation canals is critical for efficient water distribution and the prevention of leaks. This study aimed to evaluate the effectiveness of deep learning-based semantic segmentation techniques in mapping irrigation canals using satellite imagery.

Methods: For this research, a dataset of high-resolution satellite images from Khuzestan province, Iran, was collected and labeled to identify irrigation canals. Six semantic segmentation models based on deep learning were tested to detect and map the canals, with a focus on handling both regular concrete and variable earthen canals.

Results: Among the six models tested, the UNet3+ model demonstrated the highest accuracy, achieving a recall of 86.64%, an F1-score of 89.47%, and an IoU of 64.15%. The model performed well in detecting narrow and complex canal structures.

Conclusion: The findings confirm the potential of advanced deep learning methods such as UNet3+ for large-scale and accurate mapping of irrigation canals. This approach provides a practical and scalable solution for improving the monitoring and development of irrigation networks, supporting more advanced water resource management in water-scarce regions.

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Introduction

In recent years, the global water crisis has intensified (Biswas and Tortajada, 2019; Ling, 2022). Key factors contributing to this issue include climate change, revealed by rising levels of greenhouse gases such as carbon dioxide, methane, and water vapor (Haines and Patz, 2004; Naderi et al., 2024). These increases largely stem from the high consumption of fossil fuels to meet the energy demands of human societies (Haines and Patz, 2004; Loarie et al., 2009). This shift in greenhouse gas concentrations has led to significant climate alterations, including changes in precipitation patterns, finely tuned evaporation, increased transpiration, and temperature rises. The most direct impact of this phenomenon is the reduction of accessible water for drinking, industrial, and agricultural use in certain regions worldwide (Haines and Patz, 2004; Helfer et al., 2012; Trenberth, 2011).

Iran, a country with a dry climate located in Southwest Asia, has a long-standing history of agricultural civilization, where this sector plays a vital role in the economy and livelihoods across many regions. The water crisis has emerged as one of the country's most pressing challenges (Mirzavand and Bagheri, 2020). In Iran, one of the primary drivers of this crisis is the extensive consumption of water in agriculture, accounting for over 85% of the nation's water resources (Alizadeh and Keshavarz, 2005). This extensive use, combined with reduced water supplies, poses a serious risk to water availability. On the other hand, one key solution to managing this crisis is optimizing water use in the agricultural sector (Chartzoulakis and Bertaki, 2015). Irrigation canals are structures used for water transport and field irrigation. A reason for detecting and monitoring these canals is to prevent water loss and improve the efficiency of irrigation systems. These canals carry a substantial portion of the water resources for agriculture, and any defects or leaks in these systems can result in significant water losses (Moavenshahidi et al., 2016). In regions facing water scarcity, even minor losses can have considerable impacts on crop production and food security (Hamdy, 2007). Accurate monitoring and identification of canals can help optimize water distribution methods, leakage detection, and ensure equal access to water for all fields. These efforts not only increase water-use efficiency but also extend the natural life of irrigation systems. Additionally, time series detection of issues and appropriate interventions reduces maintenance and repair costs for irrigation systems. Therefore, the detection, mapping, and continuous monitoring of irrigation canals not only prevent water waste but also contribute to the long-term sustainability and improved performance of irrigation systems. Remote sensing refers to a collection of techniques and technologies used to gather and analyze data about the characteristics and changes of the Earth's surface from a distance, without requiring direct field observation of the study area (Campbell and Wynne, 2011). In recent years, this technology has become particularly significant, especially with key advancements in satellite, aerial, and drone imagery creating a powerful platform for monitoring, managing, and identifying water resources (Liu et al., 2023; Sawaya et al., 2003).

By utilizing remote sensing technology, including satellite, aerial, and drone imagery, it is possible to obtain precise and comprehensive information on agricultural irrigation networks and existing canals across various regions (Reddy et al., 2018; Waqas et al., 2019). This data encompasses the location, length, width, and physical condition of canals, aiding in the improved analysis and management of water resources. The information derived from these images supports the identification of irrigation canals and the assessment of their efficiency in water distribution across farms. Furthermore, remote sensing can effectively identify low-water-content areas and points requiring maintenance, thus enhancing water resource efficiency (Waqas et al., 2019). Additionally, remote sensing plays a crucial role in detecting and analyzing temporal changes in irrigation canals. This technology also enables the production of accurate, up-to-date maps of water canals, which can assist responsible organizations in making strategic decisions for water and agricultural resource management. In this way, remote sensing contributes to more intelligent and sustainable water resource management in agriculture and enhances resilience against water crises. With recent advancements in artificial intelligence and deep learning, researchers have leveraged neural networks for the precise extraction of image features for semantic segmentation (Cheng et al., 2020). Currently, there are two primary approaches to achieve this segmentation. The first approach consists of traditional methods that mainly rely on image processing techniques and feature extraction. These methods commonly use techniques such as edge detection, graph theory applications, clustering-based segmentation, and pixel-based segmentation (Hassanpour et al., 2011; Sathya and Manavalan, 2011). A notable limitation of these methods is the lack of semantic information in the extracted features, which can lead to inaccuracies in analysis. Furthermore, these approaches often face challenges in complex scenarios, showing poor performance due to the simplicity and limitations of the underlying algorithms. In contrast, the second approach involves advanced methods based primarily on deep convolutional neural networks (CNNs) (Liu et al., 2021). These networks are a type of deep learning model that consists of multiple complex layers of convolutional operations. In CNN models, relevant image features are automatically identified and extracted through convolutional layers, which effectively capture semantic patterns and features during the model's training stages. For a convolutional network to be properly trained and achieve high performance, it must be provided with a comprehensive and targeted dataset that enables the model to effectively learn from its input data. With recent technological advancements, especially improvements in computational power, increased data storage capacity, and progress in deep learning algorithms, there has been a significant decline in the use of traditional methods for semantic image segmentation. Instead, modern approaches based on convolutional neural networks (CNNs) have increasingly become the focus for researchers and specialists. This shift not only enhances the accuracy and efficiency of image analysis but also leads to the development of more sophisticated algorithms that improve the identification and extraction of semantic features.

Consequently, these new technologies enable far more precise image data analysis, allowing for higher-quality information extraction from images.

Despite extensive research on water‑body extraction, studies that explicitly target canals and narrow waterways remain scarce. Early work relied on multiscale CNNs such as MSR‑Net and the SegNet framework (Duan and Hu, 2019; Nath et al., 2019). Efficiency improved with the lightweight SR‑SegNet architecture (Weng et al., 2020). Subsequent advances introduced AU‑Net for the mid‑ to lower Yellow River and CoANet with a composite attention mechanism for precise river delineation (Fan et al., 2022; Liu et al., 2022). Focus then shifted to engineered channels when U‑Net was adapted for peatland drainage mapping and RAU‑Net++ was proposed for fine river branches in cold, arid regions (Robb et al., 2023; Tang et al., 2023). Most recently, hybrid data and knowledge-driven methods have emerged, combining UAV multispectral imagery with object-oriented rules and fusing PlanetScope and Google Earth imagery via the DKFNet multisource network guided by NDWI (Huo et al., 2024; Zhou et al., 2024). Altogether, multiscale architectures, attention mechanisms, and multisource fusion strategies are gradually closing the gap in accurate canal and small‑ waterway mapping.

Deep-learning models have made significant progress in mapping large lakes and wide rivers. However, current research reveals four major gaps: 1. There is limited focus on small farm canals that carry the majority of irrigation water. 2. Most studies overlook how earthen canals change over time due to erosion and agricultural activities. 3. A shortage of high-resolution images of canals that have been meticulously labeled exists. 4. There is no comprehensive and fair evaluation comparing different models using the same dataset for dry regions like Iran. To address these gaps, our study collects the first high-resolution satellite dataset of irrigation canals in Khuzestan Province, which is then hand-labeled by experts. We test six modern segmentation models, including UNet3+ and AU-Net, on this same dataset, allowing users to identify the most effective model. Additionally, we plan to maintain updated canal maps over time and develop a process that utilizes commercial satellite images to help water managers monitor large irrigation networks in near real-time.

Materials and Methods

Dataset

This province, due to its unique geographical location, has long been recognized as a vital area for agriculture and crop production. In Khuzestan province, extensive and complex irrigation systems are in place to distribute water to agricultural fields. These irrigation networks include numerous canals of varying sizes that carry water from rivers and dams to various farming fields. These canals are continuously designed to manage water resources and ensure proper water distribution across agricultural fields. The large number of irrigation canals in this province, driven by the vastness of the farms and the high demand for water resources, represents both a challenge and a strength for the region. Given the extent and distribution of the irrigation networks across the province's fields, it is considered one of the best areas to collect satellite imagery datasets of agricultural irrigation canals. For accurate boundary detection of the canals and consideration of canals with various widths, including both primary and secondary canals, some of which may not be clearly visible in satellite images. There was a need to use high-resolution satellite images. These high-resolution images also facilitate the creation of more accurate labels. As a result, Google satellite imagery was used for the dataset collection in this research. To ensure the dataset's quality, all images were carefully reviewed to eliminate those with incorrect labels, poor quality, or cloud cover. Ultimately, 1781 images remained in the dataset, with 75% of them allocated for model training and the remaining images used for evaluation. Importantly, we have to note that for reproducibility, the training and testing data assignments were clearly defined at the beginning of the process. The images in the dataset encompass a broad and diverse range of irrigation canals, concrete, and earthen. These images show a variety of canals from wide main canals to narrow secondary canals. The goal of assembling this image collection was to achieve the necessary diversity in canal structures. Therefore, the deep learning models could optimally identify these features. In the image labeling process, several challenges were encountered that impacted the accuracy and quality of the dataset. One of the primary issues was the presence of shadows in the images, which could significantly obscure the boundaries of the canals, making them difficult to identify. Additionally, another challenge was distinguishing the boundaries of earthen canals and the surrounding land, as natural or man-made features near the canals could be similar, leading to errors in labeling. Moreover, the presence of geographic and structural features such as trees, buildings, and other environmental elements could complicate the correct identification of the canals. These factors not only made the labeling process more difficult but could also reduce the accuracy of deep learning models in identifying and analyzing irrigation canals. Data augmentation techniques were employed. One such technique was flipping the images vertically, which helped increase data variety and reduce the likelihood of overfitting. Moreover, rotating the images at different angles improved the model's ability to identify objects from various perspectives, making it more robust against diverse viewing angles. Figure 1 shows sample images from the dataset.

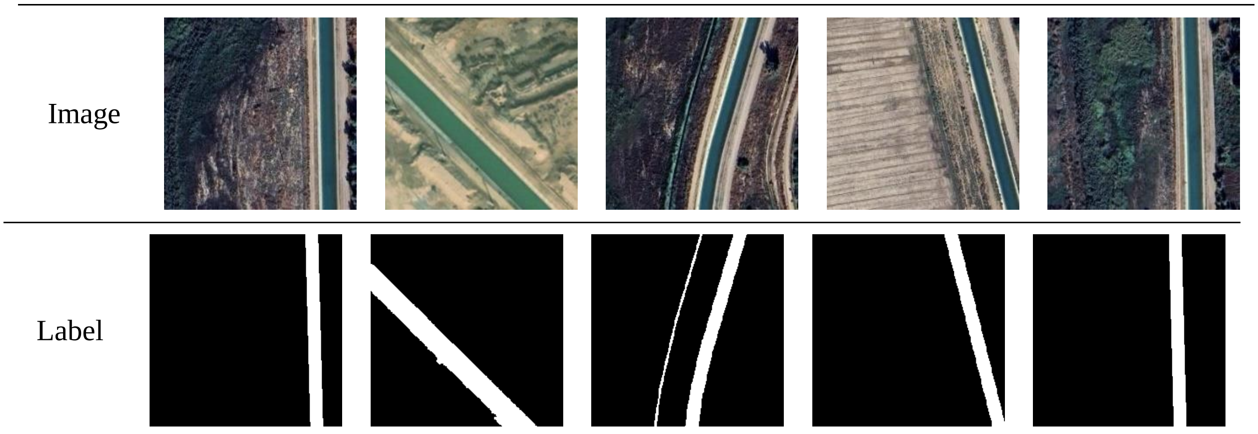


Figure 1. Samples of the canals dataset images.

Methodology

In this research, six deep learning networks were employed for the semantic segmentation of agricultural irrigation canals. First, a set of images related to agricultural irrigation canals was downloaded, which included diverse samples representing different environmental conditions and types of canals.

The collected images underwent a preprocessing stage to ensure their suitability for training the deep learning models. This stage involved tasks such as light correction, removal of noisy images, normalization, and cropping of the images. The dataset was then divided into two parts: training and validation. Data augmentation techniques were applied to the training data to increase the number of images. Each of the six deep learning networks was independently trained using the preprocessed data. The training process included various settings, including hyper-parameter tuning. Finally, the performance of the trained models was evaluated using different assessment metrics. Figure 2, illustrates the corresponding flowchart and the steps involved in conducting the research.

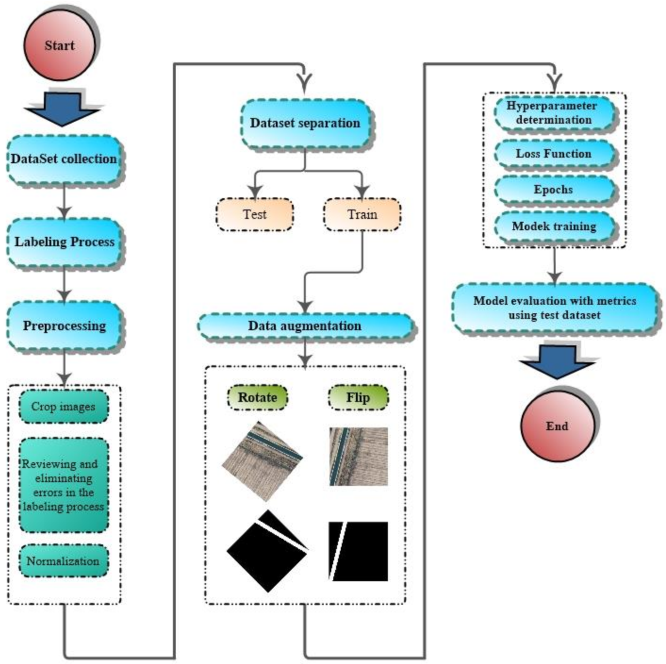


Figure 2. Flowchart of the research process.

Deep Learning Networks

This section introduces and explains the architectures of deep learning networks utilized in this research for semantic segmentation. These networks, employing layered structures and connections between layers, are specifically designed for the task of semantic segmentation of agricultural irrigation canals. In general, all the networks used have two paths for segmentation. First, the feature map is generated from the input image during the encoding process. The feature map contains valuable and necessary information for segmentation, which is processed in the decoding path to produce the final output. Figure 3, shows the overall structure of the deep learning networks.

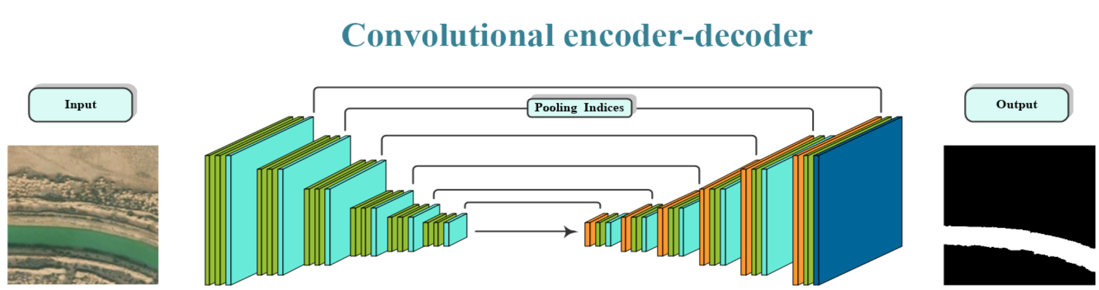


Figure 3. Overall structure of deep learning networks.

BiSeNet

BiSeNet (Bilateral Segmentation Network) is an architecture designed for semantic segmentation tasks (Yu et al., 2018). The BiSeNet model includes two main paths: the spatial path and the context path. The spatial path is responsible for preserving fine details with high resolution from the input image. This path uses a series of convolutional layers to reduce the image size while maintaining crucial spatial information, ensuring that fine details are not lost during processing. In contrast, the context path is designed to extract more abstract and high-level features from the image. In the implementation, this path uses a pre-trained ResNet-50 as the backbone, which extracts deep features at various scales. These features are then enhanced using Attention Refinement Modules (ARMs), which focus on more important parts of the feature maps. The outputs of the context path are scaled up and combined with the outputs from the spatial path to integrate both precise information and contextual information. The final step of BiSeNet involves a feature fusion module that merges the outputs from both paths. This fusion process incorporates attention mechanisms, which highlight important features while suppressing less relevant ones, leading to a more accurate segmentation output.

LinkNet

The LinkNet architecture for segmentation is designed with a dual structure: an encoder and a decoder (Chaurasia and Culurciello, 2017). The encoder focuses on extracting important features from the input image while gradually reducing its dimensions. This is achieved through a series of convolutional blocks, each followed by MaxPooling2D layers to reduce the image size. The encoder uses convolutional layers with increasing filter counts to extract hierarchical features at various levels. In contrast, the decoder is responsible for reconstructing the image back to its original dimensions. This is done using Conv2DTranspose layers to upsample the image and recover detailed features. Skip connections between corresponding layers in the encoder and decoder help preserve spatial accuracy by combining high-resolution features with the upscaled outputs. This approach ensures that important spatial details are retained and accurately reflected in the final output.

DeepLabV3+

The DeepLabV3+ architecture improves feature extraction and processing using several key components (Chen et al., 2018). The core of the network is the ResNet50 model, which provides a hierarchical set of features from the input image. In the ASPP (Atrous Spatial Pyramid Pooling) section, the model processes these high-level features using convolutional layers with different atrous rates. This capability allows the network to capture both fine details and broader contextual information. Specifically, the ASPP module includes branches for extracting global features, 1×1 convolutions, and atrous convolutions with rates of 6 and 12. These branches are combined to create a comprehensive feature representation. Additionally, this multi-scale feature extraction is achieved without a significant increase in computational complexity.

The decoder section in DeepLabV3+ is designed to increase the dimensionality of the feature maps to the original image size. This is done using upsampling layers, which enlarge the spatial dimensions. Low-level features obtained from the earlier stages of the ResNet-50 model are used to improve the preservation of details in this process. These features undergo a series of convolutions, batch normalization, and ReLU activations to refine and combine the multi-scale features. Finally, the refined and upsampled feature maps are processed through a 1×1 convolution and then an activation function. The architecture of the DeepLabV3+ network is illustrated in Figure 4.

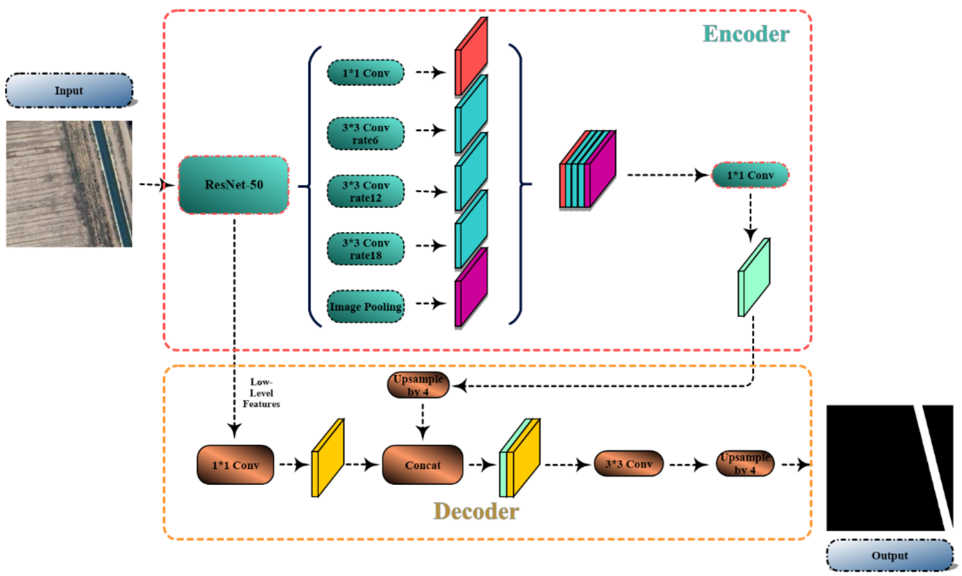


Figure 4. Overall architecture of the DeepLabV3+

FCN

The FCN model consists of a sequence of convolutional layers that progressively reduce the dimensions of the input image while extracting important features at each stage (Long et al., 2015). The initial layers of the network extract low-level details, while each subsequent layer identifies more complex features. To maintain high-resolution spatial information, the model utilizes a series of Conv2D layers followed by Batch Normalization, each followed by a ReLU activation function. As the network reduces the image dimensions, the feature maps obtained at various stages are stored for later use in the upsampling process. These stored feature maps are useful for preserving fine details in the final segmentation output. In the upsampling stage, the model uses Conv2DTranspose layers to restore the image dimensions to their original size. In this process, the stored feature maps are reintroduced via skip connections, which help preserve important spatial details that may have been lost during downsampling. These skip connections are crucial for achieving accurate segmentation, as they allow the model to combine both high-level information and fine details. The final network output is produced through a Conv2DTranspose layer with a sigmoid activation function.

PSPNet

The PSPNet (Pyramid Scene Parsing Network) is a convolutional neural network (CNN) architecture (Zhao et al., 2017). The key component of this network is the pyramid pooling module. This module includes several parallel pooling layers with different network sizes. Each pooling layer collects information at a specific scale, capturing both fine and global context. The feature maps obtained from these pooling layers are then concatenated and used for further processing. This process allows the network to gain a deeper understanding of the spatial relationships between objects in the image. It can identify more precise features that play a crucial role in achieving accurate segmentation. Overall, PSPNet can be built upon various architectures, such as different versions of ResNet. The architecture of the PSPNet network is depicted in Figure 5.

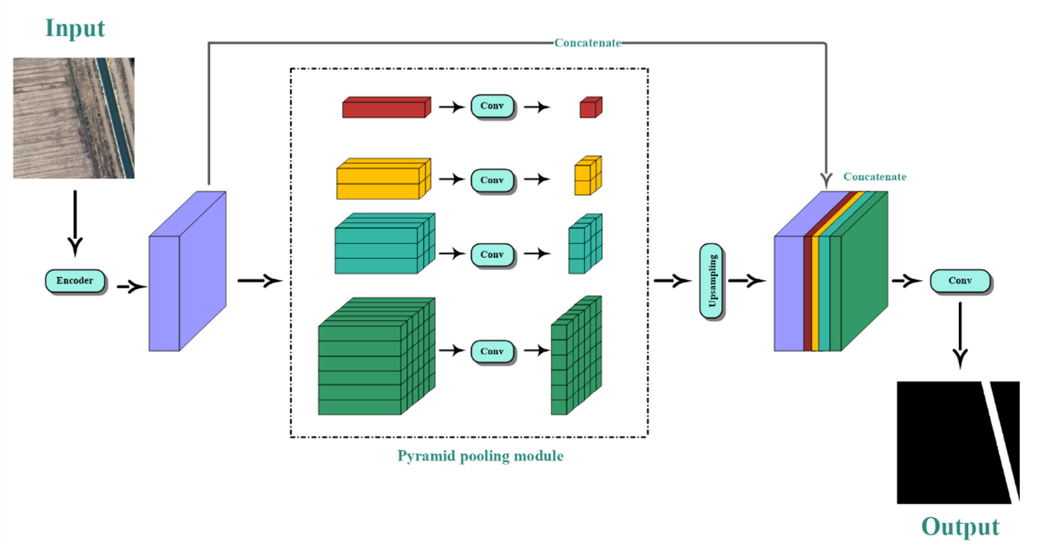


Figure 5. Overall architecture of the PSPNet.

UNet3+

The UNet3+ architecture is built upon the initial design of U-Net and has been enhanced to improve accuracy in semantic segmentation (Huang et al., 2020). This network has an encoder-decoder structure, where skip connections have been redesigned to improve the flow of information. The encoder section consists of several convolutional blocks, each accompanied by a max-pooling layer to reduce the dimensions of the input image. These blocks gradually extract higher-level features from the image. Block 1 processes the initial input, while blocks 2 to 5 extract deeper and more abstract features by progressively reducing the dimensions of the feature maps. At the deepest level, the bottleneck layer (block 5) extracts more abstract features from the input. The decoder section reconstructs the segmentation map by upsampling the feature maps from the bottleneck. The decoder includes several upsampling stages, where, in each stage, the features from the corresponding layers in the encoder are merged with the upsampled features. This approach allows for the integration of fine details with the global context of the image. The innovation of UNet3+ lies in the redesign of the skip connections. These connections link the encoder and decoder layers within the same block and across multiple resolutions. At each stage of the decoder, features from different scales are merged, improving the segmentation accuracy by combining detailed information with contextual information. Figure 6, shows the architecture of this network.

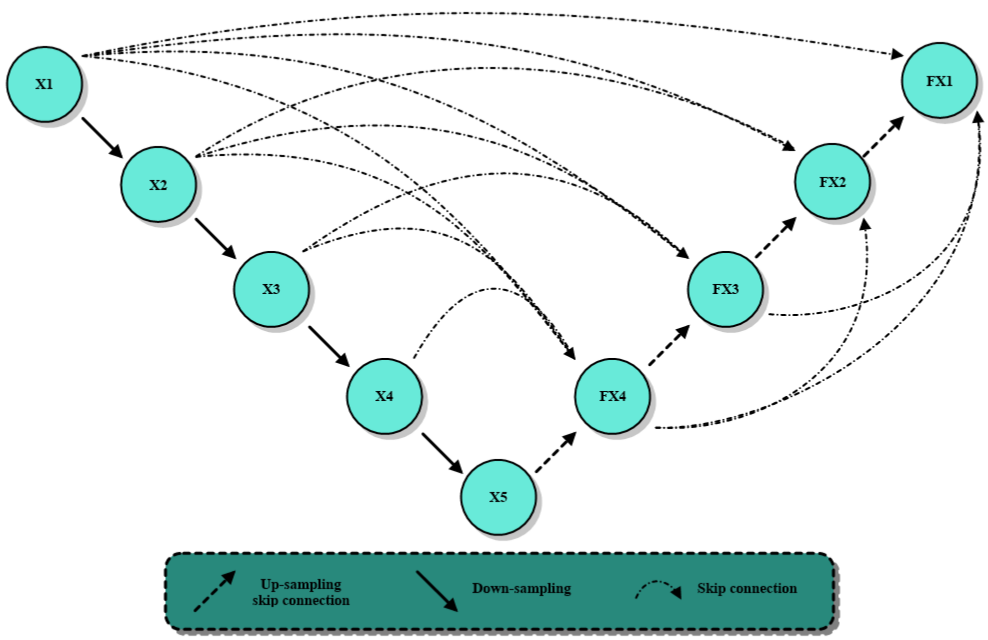


Figure 6. Overall architecture of the UNet3+

Evaluation Metrics

In this research, evaluation metrics are used to assess the performance of deep learning models, and this section aims to introduce and explain these metrics. Common evaluation indices, widely utilized in many deep learning studies, have been employed to measure the accuracy and quality of semantic segmentation in agricultural irrigation canals. The purpose of this section is to provide a comprehensive explanation of each of these metrics and how they are applied in evaluating the performance of the models.

IoU

The Intersection over Union (IoU) is an evaluation metric that measures the overlap between the predicted segmentation mask and the ground truth mask. This metric is calculated by finding the ratio of the area of overlap (i.e., the intersection) between the correctly identified pixels in both masks to the area of the union of all pixels in both masks. The total area includes pixels that are correctly identified (true positives, TP), pixels incorrectly identified as foreground (false positives, FP), and pixels incorrectly labeled as background (false negatives, FN). The IoU can be calculated using equation (1):

$$\mathrm{IoU} = \frac{TP}{TP + FP + FN} \tag{1}$$

Recall

In the context of image segmentation, the Recall evaluation metric measures the percentage of pixels that have been correctly identified by the model as belonging to a specific class, relative to the total number of actual pixels in that class. Generally, this metric evaluates the model's ability to fully identify all instances of a particular class. A higher value of Recall indicates the model's ability to accurately identify all the target class pixels, while a lower value suggests the model's inadequacy in identifying all these pixels. Increasing errors in the model's ability to correctly classify the target class, such as incorrectly labeling true positive pixels as negative, results in a lower Recall value. The Recall metric is calculated using equation (2):

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

Precision

The Precision metric evaluates the accuracy of a model in correctly identifying positive pixels. It calculates the ratio of the number of background pixels that have been correctly identified as background (True Positives, TP) to the total number of pixels that have been identified as background (True Positives and False Positives, FP). The Precision is calculated using equation (3):

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

F1-score

The F1-score is an evaluation metric for semantic image segmentation that measures the similarity between the predicted segmentation mask and the ground truth mask. It combines the Precision and Recall metrics into a single score to provide a balanced measure of the model's performance, especially when the class distribution is imbalanced. The F1-score is calculated using equation (4):

$$F1\text{-}score = \frac{2TP}{2TP+FP+FN} \quad (4)$$

Loss Function

The Binary Cross-entropy loss function is a commonly used evaluation metric in binary classification problems. It measures the difference between the predicted probabilities and the actual values. In binary classification tasks, the model typically outputs a probability for each class (usually 0 or 1). Binary Cross-entropy calculates the error based on the difference between the predicted probability and the actual value, aiding in adjusting the model's weights during the learning process. The Binary Cross-entropy loss is calculated using equation (5):

$$L\,(y,\hat{y}) = -\frac{1}{N}\sum_{i=0}^{N}(y_i \times log(\hat{y}_i) + (1-y_i) \times log(1-\hat{y}_i)) \quad (5)$$

The symbol N represents the total number of samples, y and $\hat{y}_i$ denote the actual labels and the predicted probability vector, respectively.

Hyperparameters

Hyperparameters in Convolutional Neural Networks (CNNs) refer to values that need to be set and adjusted before the training process begins. These parameters have a significant impact on the performance and efficiency of the network. In this research, the hyperparameters for the neural network have been set as follows:

- Learning Rate: 0.003
- Batch Size: 4
- Epochs: 100
- Optimizer: Adam

These values were chosen based on their potential to optimize the performance of the network in the specific context of this research.

Results and Discussion

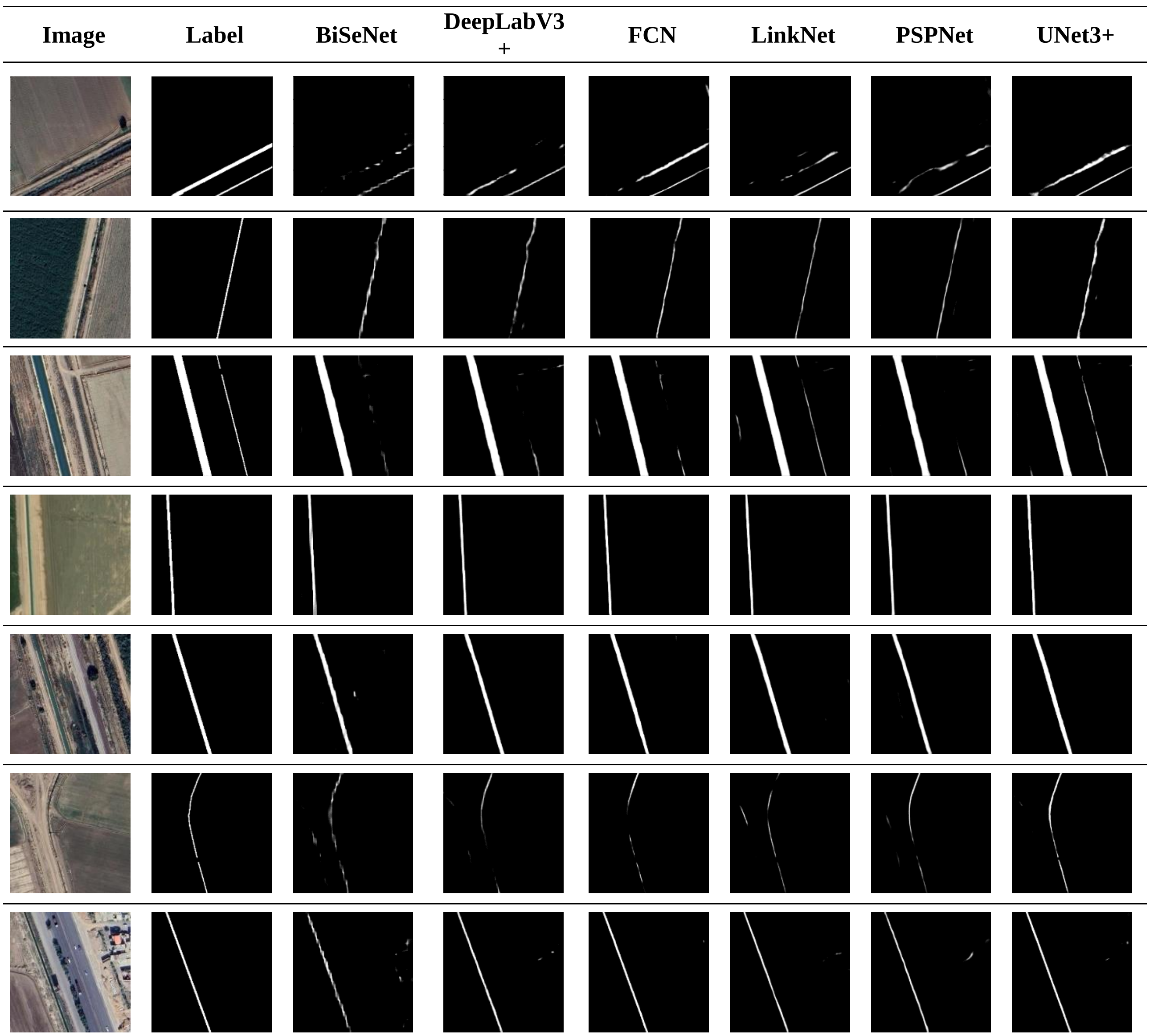
The comparative evaluation of multiple deep learning architectures for the task of irrigation canal segmentation reveals clear performance differences across models. Among the networks tested, Unet3+ consistently demonstrated superior results in Recall, IoU, and F1-score metrics, suggesting that Unet3+ is more effective at identifying both the presence and boundaries of irrigation canals, particularly in complex visual settings. While LinkNet achieved the highest Precision (93.96%), its lower Recall (compared to Unet3+) indicates that although it precisely identified many canal pixels, it missed a portion of narrower or less visible canals, highlighting the importance of evaluating segmentation models with balanced metrics such as F1-score, rather than relying solely on Precision. The strength of Unet3+ can be attributed to its multi-path skip connections, which can effectively leverage both low-level and high-level features. This structural advantage enhances the network's ability to detect subtle visual cues, especially in areas where canals are visually similar to the background—such as earthen canals that blend into agricultural soil or appear beneath vegetation shadows. These canals are particularly challenging to segment due to their thin structure, spectral similarity with surroundings, and irregular shapes. The qualitative results, illustrated in Figures 7 to 9, further support the quantitative findings, showing Unet3+ producing more continuous and accurate canal boundaries.

These findings offer additional insights. In the study by Wang et al. (2022), semantic segmentation of rivers using LinkNet and other models yielded strong results. However, the application context was limited to relatively well-defined water bodies like rivers. In contrast, our dataset includes narrow, shallow, and visually complex canal structures, especially earthen irrigation canals, where previous models tend to underperform. This highlights a notable gap in the literature, where most segmentation models are developed for natural water bodies and not engineered water infrastructure. Furthermore, earthen canals, due to erosion and seasonal change, require frequent mapping, which cannot be addressed efficiently through manual field surveys. The ability of Unet3+ to generalize well across different canal types and conditions makes it a promising tool for real-world applications such as precision agriculture, water resource monitoring, and digital twin irrigation management systems. Despite these strengths, some limitations remain. The current approach relies solely on RGB satellite imagery, which may be sensitive to seasonal variations, lighting conditions, or occlusions by vegetation. Future work can benefit from the integration of multispectral data, temporal image series, or LiDAR information to further improve robustness. Additionally, transfer learning and domain adaptation techniques could be explored to apply the trained model to new geographic regions with minimal retraining.

In summary, this study provides a comprehensive benchmark and performance analysis of various semantic segmentation models for irrigation canal mapping. It demonstrates that Unet3+ offers the best trade-off between detection accuracy and detail preservation, particularly in visually complex agricultural environments. These results have both academic relevance and practical significance in addressing water resource management challenges under increasing global water scarcity.

Table 1. Evaluation Results of Semantic Segmentation Networks on Irrigation Canal.

Network	Evaluation Metrics			
	F1-score	IoU	Recall	Precision
BiSeNet	87.20	55.84	83.35	91.42
DeepLabV3+	89.02	61.25	85.69	92.63
FCN	89.05	61.50	85.17	93.31
LinkNet	88.53	61.69	83.69	93.96
PSPNet	86.42	59.88	83.09	90.03
Unet3+	89.47	64.15	86.64	92.49



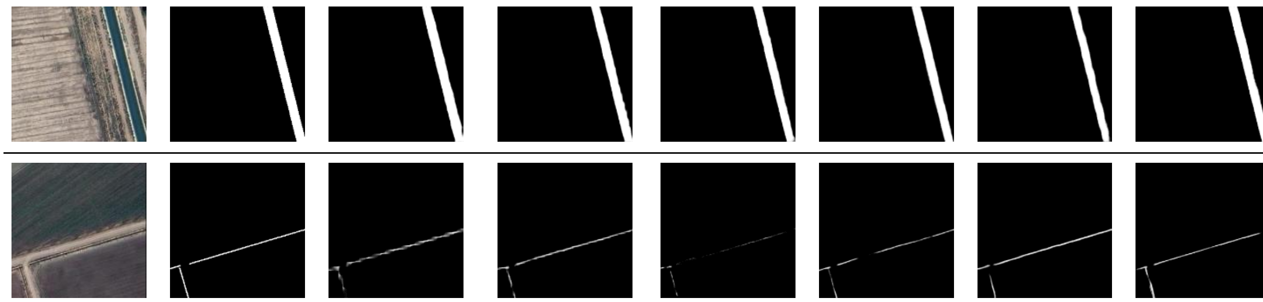


Figure 7. Output of Convolutional Networks for Irrigation Canal Images.

Image	Label	BiSeNet	DeepLabV3+	FCN	LinkNet	PSPNet	UNet3+

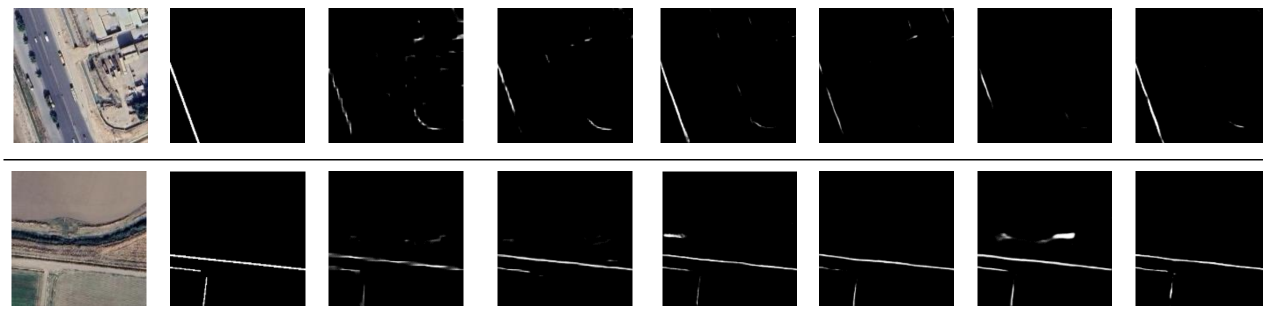
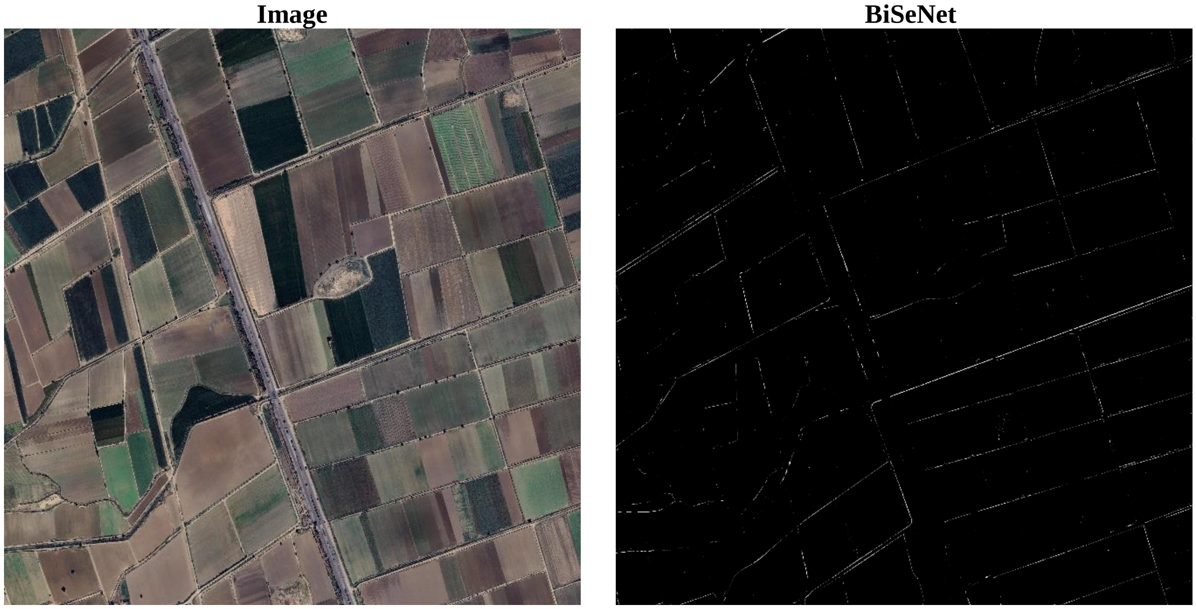
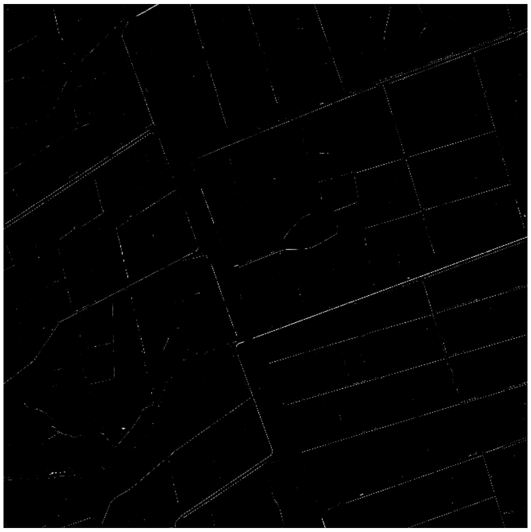
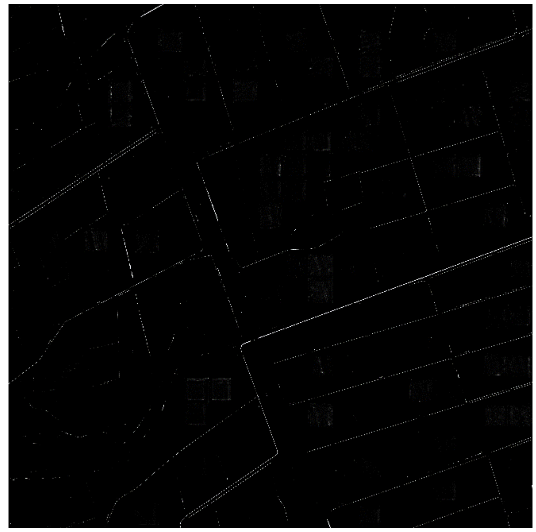


Figure 8. Comparison of Output Images from Convolutional Networks.

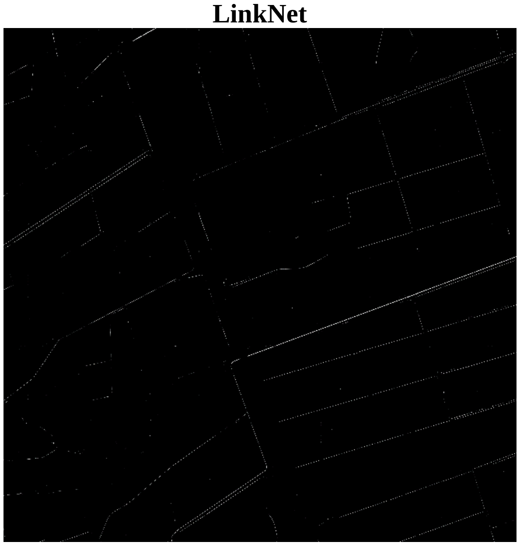
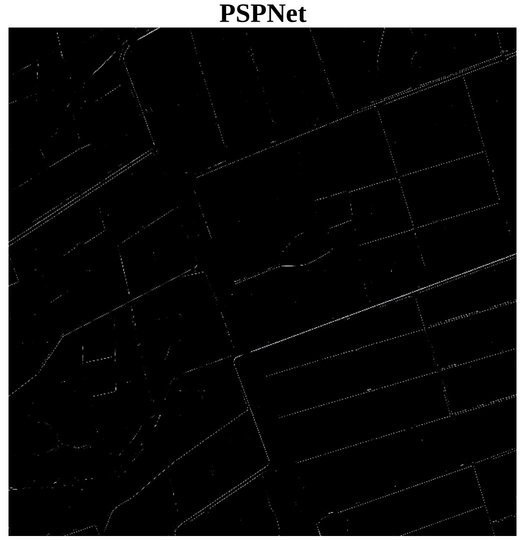
Image	BiSeNet



DeepLabV3+	FCN

LinkNet **PSPNet**

UNet3+

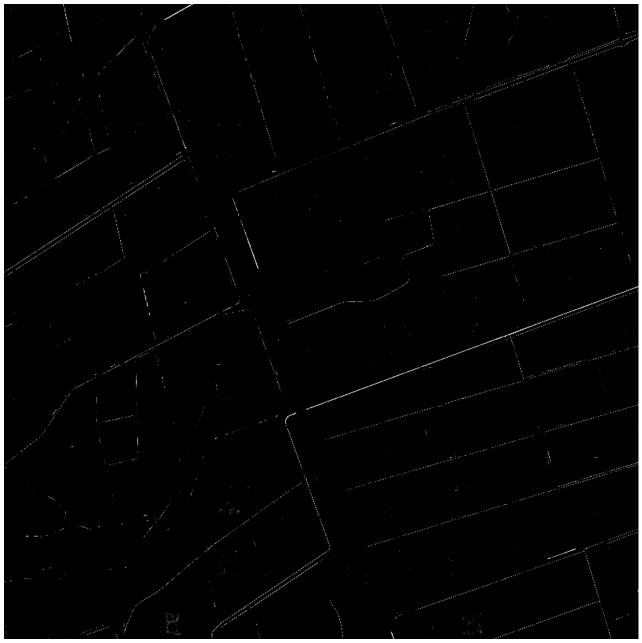


Figure 9. The irrigation canal network.

Conclusion

The present research investigates and evaluates deep learning methods for the semantic segmentation of satellite images, identifying agricultural irrigation canals. In this research, a dataset consisting of satellite images of irrigation canals in Khuzestan Province was collected, with corresponding labels for each image provided in two classes. After preparing a suitable dataset, six convolutional neural networks were trained on this dataset. The results showed that the UNet3+ network outperformed other models under review. With Recall and F1-score values of 86.64% and 89.47%, respectively, this network was particularly successful in accurately identifying narrower earthen canals and more complex areas compared to other networks.One of the main reasons contributing to the superiority of Unet3+ is its ability to transfer key information from all encoder layers to the decoder. This capability enhances the performance and accuracy of identifying the boundaries of narrow irrigation canals and finer segments, demonstrating a significant improvement over other models such as BiSeNet and DeepLabV3+. Additionally, with this architecture, the network has managed to detect a wider variety of complex features in satellite images, achieving superior performance with an IoU score of 64.15%. It is noteworthy that while the LinkNet model performed better in terms of Precision, Unet3+ emerged as the best model in this research due to its balanced performance across various evaluation metrics and high accuracy in detecting irrigation canals of different widths and their boundaries. This research effectively addresses common challenges in identifying and mapping irrigation canals using high-resolution satellite imagery and quality data, offering an optimized method for highly accurate detection of these irrigation canals. Mapping of earthen irrigation canals, especially in regions like Khuzestan Province with widespread irrigation networks, is of high importance. Unlike concrete canals, which typically have stable and precise mapping, earthen canals often lack formal and up-to-date maps due to natural changes over time, such as shifts in course or alterations in dimensions. Manual mapping of these canals can be both costly and time-consuming. However, deep learning-based methods, such as semantic segmentation, enable the creation of precise and fast mapping. This approach can simulate the current state of the canal network with high accuracy, contributing to the optimal management of irrigation resources. Ultimately, this research demonstrates the strong capabilities of Unet3+ in the semantic segmentation of satellite images, offering an effective solution for the accurate identification and mapping of agricultural irrigation canals in regions with similar characteristics.

Better capture surface features and water canals, and develop and implement more advanced models for enhanced accuracy in identifying complex areas. Additionally, expanding the dataset is recommended to evaluate model performance across diverse geographical and climatic regions with varying geological characteristics, thereby improving the generalizability and robustness of the findings. The results of this research hold significant potential for application in water resource management and agricultural irrigation. By leveraging these findings, managers and decision-makers can improve the monitoring and control of irrigation canals, optimize water usage planning, and reduce water loss due to evaporation and mismanagement. Furthermore, this work can be extended to broader applications, such as identifying water scarcity regions, designing and routing new irrigation networks, and improving water conservation strategies. It is hoped that these insights will be valuable for researchers and professionals striving to achieve sustainable water management practices.

Author Contributions

All authors contributed equally to the conceptualization of the article and writing of the original and subsequent drafts.

Data Availability Statement

Data available on request from the authors.

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Ethical considerations

The authors avoided data fabrication, falsification, plagiarism, and misconduct.

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Conflict of interest

The authors declare no conflict of interest.

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