u-net for medical image processing

U-Net for Medical Image Processing: A Comprehensive Review

1. Introduction: The Rise of U-Net in Medical Imaging

This paper provides a comprehensive review of the U-Net architecture and its numerous variants within the context of medical image processing. We will explore the foundational U-Net model [1], its inherent strengths and limitations, and the diverse modifications proposed to enhance its performance across various medical imaging modalities. The review will analyze the impact of these modifications on accuracy, efficiency, and applicability to different clinical tasks. We will also discuss the challenges and future directions of U-Net-based medical image segmentation. The success of U-Net stems from its ability to effectively handle high-resolution images and accurately segment small objects, crucial aspects in medical image analysis where fine details often hold diagnostic significance [1], [2]. However, the original architecture presents limitations, including potential information loss during downsampling and a sensitivity to hyperparameter tuning that can significantly affect performance [2], [3]. This review will systematically examine the extensive body of research dedicated to addressing these limitations and exploring the vast potential of U-Net in various medical applications.

2. The Foundational U-Net Architecture and its Core Principles

The original U-Net architecture [1] introduced a novel encoder-decoder structure specifically designed for biomedical image segmentation. The encoder pathway progressively downsamples the input image using convolutional layers, capturing increasingly abstract semantic features at each level. Simultaneously, max-pooling operations reduce the spatial dimensions, resulting in a compressed representation of the input. Crucially, the decoder pathway mirrors the encoder, upsampling the feature maps through transposed convolutions and concatenating them with corresponding feature maps from the encoder via skip connections [1]. These skip connections play a vital role in preserving spatial information lost during downsampling, enabling the network to reconstruct fine details in the segmentation output [1]. The architecture’s U-shape is a direct consequence of this mirrored encoder-decoder structure and the strategic use of skip connections [1].

The advantages of this design are manifold. The encoder's hierarchical structure allows the network to learn multi-scale features, effectively capturing both global context and fine details. The skip connections prevent the loss of fine-grained spatial information that would otherwise occur with repeated downsampling [1]. This makes U-Net particularly effective in segmenting small objects, a common challenge in medical image analysis where subtle anomalies can hold significant clinical relevance [2]. The architecture's relatively straightforward design also contributes to its ease of implementation and training [1].

However, the U-Net architecture is not without limitations. The use of max-pooling in the encoder can lead to information loss, potentially hindering the accuracy of segmentation, especially in regions with fine details [2]. Furthermore, the performance of U-Net is sensitive to hyperparameter tuning, requiring careful optimization to achieve optimal results across diverse datasets and tasks [3]. The reliance on skip connections, while beneficial, can also introduce limitations in the fusion of multi-scale features, potentially leading to suboptimal integration of information from different levels of the network [4]. These limitations have motivated the development of numerous U-Net variants, each aimed at addressing specific weaknesses and enhancing performance in particular applications.

3. Addressing U-Net's Limitations: A Survey of Architectural Modifications

The inherent strengths and limitations of the original U-Net architecture have spurred a prolific body of research dedicated to improving its performance and expanding its applicability. The modifications proposed can be broadly categorized into several key areas: enhancing skip connections and feature fusion, incorporating attention mechanisms, exploiting recurrent and residual connections, leveraging transformer architectures, optimizing network depth and width, and improving loss functions and optimization strategies. We will delve into each of these categories in detail.

3.1. Enhancing Skip Connections and Feature Fusion

A significant focus of U-Net variant research has been on improving the efficiency and effectiveness of skip connections in facilitating multi-scale feature fusion. The original U-Net's simple concatenation of encoder and decoder features, while effective, can be improved upon. U-Net++ [4] addresses this by redesigning the skip connections to create a more sophisticated multi-level aggregation scheme. Instead of simple concatenation, U-Net++ introduces dense skip connections, allowing features from multiple scales to be aggregated at each level of the decoder. This more nuanced approach allows for a richer integration of multi-scale information, enhancing the network's ability to capture both global context and fine details [4].

U-Net v2 [5] takes a different approach, focusing on augmenting the infusion of semantic information from higher-level features into the lower-level ones. It achieves this by employing the Hadamard product to combine high-level semantic features with low-level detail features at each level. This method allows for a more refined incorporation of semantic information, potentially improving the accuracy of segmentation, particularly in complex scenarios [5]. The multi-scale feature fusion strategy employed in MA-Net [6] also enhances performance by combining features from different scales in a more sophisticated manner. This is achieved through a combination of position-wise attention and multi-scale feature aggregation blocks, facilitating more effective integration of multi-scale information [6].

3.2. Incorporating Attention Mechanisms

The integration of attention mechanisms has emerged as a powerful strategy for improving the performance of U-Net architectures. Attention mechanisms allow the network to focus on the most relevant parts of the input image, effectively suppressing irrelevant background information and emphasizing regions of interest. Attention U-Net [7] is a prime example, incorporating attention gates into the skip connections to dynamically weigh the importance of different feature maps. This enables the network to selectively emphasize relevant features, enhancing segmentation accuracy, particularly in challenging scenarios with cluttered backgrounds [7].

The Spatial-Channel Attention Gate [8] further refines this approach by integrating spatial and channel-wise attention mechanisms. This allows the network to attend to both spatial locations and feature channels, leading to a more nuanced and effective attention mechanism [8]. The Global Attention Mechanism (GAM) in GAM-UNet [9] provides another example, automatically adjusting the weights of feature maps to focus on relevant regions. This approach improves segmentation accuracy by directing the network's attention towards the target areas, effectively reducing the influence of irrelevant background information [9]. MN-Unet [10] integrates attention mechanisms into a transformer architecture, combining the benefits of both approaches for improved performance. The multi-scale nature of the attention mechanism in MN-Unet allows the network to capture both local and global contextual information, enhancing its ability to segment objects of varying sizes and complexities [10].

3.3. Exploiting Recurrent and Residual Connections

Recurrent and residual connections have been incorporated into U-Net to address the vanishing gradient problem, a common issue in deep neural networks that can hinder training and performance. The vanishing gradient problem occurs when gradients become extremely small during backpropagation, making it difficult for the network to learn effectively [3]. Recurrent connections, as used in R2U-Net [11], [7], allow the network to process information sequentially, accumulating features over time and improving feature representation. This approach helps to mitigate the vanishing gradient problem and allows the network to learn more robust representations of the input data [11], [7].

Residual connections, as incorporated in Residual-Attention UNet++ [12], provide another effective strategy. Residual connections allow the network to learn residual mappings, effectively bypassing certain layers and facilitating the flow of gradients during training [12]. This approach helps to address the vanishing gradient problem and allows the network to learn deeper representations of the input data. LadderNet [13] combines recurrent and residual connections to create a chain of multiple U-Nets, further enhancing the network's ability to learn complex features and improve segmentation accuracy [13]. The use of residual blocks in LadderNet is inspired by the success of ResNet and R2-UNet, demonstrating the effectiveness of these techniques in improving U-Net performance [11], [13].

3.4. Leveraging Transformer Architectures

Transformer architectures, initially developed for natural language processing, have recently gained popularity in computer vision due to their ability to capture long-range dependencies and global context [14]. This capability is particularly beneficial in medical image segmentation, where understanding the relationships between distant regions of an image can be crucial for accurate segmentation.

TransUNet [14] effectively combines the strengths of transformers and U-Net, using transformers as encoders to capture global context and U-Net's decoder for precise localization. This hybrid approach allows the network to leverage the global context modeling capabilities of transformers while retaining the detailed spatial information preservation of U-Net [14].

DS-TransUNet [15] extends this approach by integrating Swin transformers into both the encoder and decoder. This allows the network to capture multi-scale contextual information throughout the entire process, leading to improved segmentation accuracy [15]. The dual-scale encoding mechanism in DS-TransUNet, employing both coarse and fine-grained feature representations, further enhances the network's ability to handle images with varying levels of detail [15]. Mixed Transformer U-Net (MT-UNet) [16] incorporates a Mixed Transformer Module (MTM) for simultaneous inter- and intra-sample affinity learning. This allows the network to learn both within-sample and between-sample relationships, further enhancing its ability to capture global context and improve segmentation performance [16].

3.5. Optimizing Network Depth and Width

The optimal depth and width of the U-Net architecture are often task-specific and not easily determined a priori. Manually tuning these hyperparameters can be time-consuming and may not yield optimal results. AdwU-Net [17] addresses this challenge by proposing a differentiable neural architecture search framework. This framework automatically searches for the optimal depth and width of the U-Net architecture for a given task, significantly reducing the need for manual hyperparameter tuning [17]. The adaptive depth and width blocks in AdwU-Net allow for a more efficient and effective search process, leading to architectures tailored to specific tasks and datasets [17].

Other studies explore alternative strategies for network design. Half-UNet [18] simplifies the U-Net architecture by reducing the number of layers in both the encoder and decoder pathways. This results in a significantly smaller and more efficient network, suitable for deployment on resource-constrained devices [18]. The Modified Double U-Net [19] employs an ensemble learning approach, stacking two U-Nets to leverage the strengths of multiple models. The first U-Net utilizes an ensemble of pre-trained models (Xception, DenseNet, and VGG-19), while the second U-Net captures additional information for semantic segmentation [19].

3.6. Improving Loss Functions and Optimization Strategies

The choice of loss function and optimization strategy can significantly impact the performance of U-Net models. The standard cross-entropy loss function may not be optimal for all medical image segmentation tasks, particularly those with imbalanced datasets. The Hybrid Dice Focal Loss (HDF loss) in HDFU-Net [20] addresses this by combining the Dice loss and focal loss to improve segmentation accuracy, especially for imbalanced datasets [20]. The Dice loss is particularly effective in handling class imbalance, while the focal loss down-weights the contribution of easily classified samples, focusing the training process on more challenging cases [20].

Similarly, the exponential logarithmic loss used in a Multi Scale Supervised 3D U-Net [2], [21] is specifically designed to alleviate the negative effects of sample imbalance in kidney and tumor segmentation tasks [2], [21]. Different optimizers can also significantly affect training performance. The use of AdamW in MAGRes-UNet [22], for example, demonstrates improved performance compared to the standard Adam optimizer [22]. The choice of activation functions also plays a role, with Mish and ReLU being compared in MAGRes-UNet [22], showing that Mish combined with AdamW provides significant performance improvements [22].

4. Applications of U-Net and its Variants in Medical Image Segmentation

The versatility of U-Net and its variants has led to their widespread adoption across various medical imaging modalities and clinical tasks. We will explore some of the key applications, highlighting the specific challenges and successes of U-Net-based approaches in each domain.

4.1. Brain Tumor Segmentation

Brain tumor segmentation from MRI images is a critical task in oncology, aiding in diagnosis, treatment planning, and prognosis. The complex shapes, textures, and varying sizes of brain tumors pose significant challenges for automated segmentation. U-Net and its variants have been extensively applied to this task, demonstrating significant improvements in accuracy over traditional methods [23],

[24], [20]. Studies such as [23] have shown that U-Net-based models can achieve high accuracy in segmenting different tumor sub-regions, including the whole tumor, tumor core, and enhancing tumor [23]. The challenges inherent in this task, such as the high variability in tumor appearance and the presence of ambiguous boundaries, have driven the development of specialized U-Net architectures tailored to the specific characteristics of brain tumors [24], [20].

4.2. Organ Segmentation

Accurate organ segmentation is essential for various clinical applications, including radiotherapy planning, surgical simulation, and disease monitoring. U-Net's ability to handle high-resolution images and segment small structures makes it well-suited for this task. It has been successfully applied to segmenting a wide range of organs, including the liver [6], kidneys [2], [21], prostate [25], and heart [26]. The challenges in organ segmentation vary depending on the organ and imaging modality. For instance, the liver's complex internal structure and variations in appearance across different patients can make accurate segmentation challenging [6]. Multi-modal approaches, such as MPU-Net [25], have been developed to leverage the complementary information from multiple imaging modalities, improving the accuracy and robustness of organ segmentation [25].

4.3. Lesion Detection and Segmentation

Detecting and segmenting lesions, such as skin lesions [3], [19], [22], lung nodules [18], and polyps [5], [19], is crucial for early diagnosis and treatment. U-Net's ability to learn complex patterns and segment small objects makes it a valuable tool in this domain. The challenges in lesion detection and segmentation include the variability in lesion size, shape, and appearance, as well as the presence of noise and artifacts in medical images [3], [19]. Specialized U-Net architectures have been developed to address these challenges, often incorporating attention mechanisms, recurrent connections, or other modifications to improve performance [3], [19].

4.4. Other Applications

The applicability of U-Net extends beyond these major applications. It has been successfully employed in diverse medical image segmentation tasks, including nerve segmentation in ultrasound images [27], spine segmentation [7], and dental X-ray image segmentation [28], [29]. The versatility of U-Net stems from its ability to adapt to different imaging modalities and segmentation tasks, making it a valuable tool across various medical imaging domains. For example, the segmentation of intervertebral discs from MR spine images [30] presents a unique challenge due to the fine details and complex boundaries involved. Specialized U-Net architectures, such as BSU-Net [30], have been developed to address this challenge, achieving higher accuracy than the standard U-Net architecture [30]. Similarly, the segmentation of fish images [31] demonstrates the adaptability of U-Net to non-medical image processing tasks, highlighting its broader potential beyond medical applications [31].

5. Evaluation Metrics and Benchmark Datasets

Evaluating the performance of U-Net and its variants requires appropriate metrics and benchmark datasets. Commonly used metrics include the Dice coefficient, Intersection over Union (IoU), and accuracy. The Dice coefficient measures the overlap between the predicted segmentation and the ground truth, providing a measure of segmentation accuracy [7], [28], [29]. IoU, also known as Jaccard index, calculates the ratio of the intersection to the union of the predicted and ground truth segmentations, providing another measure of segmentation accuracy [7], [28], [29]. Accuracy simply measures the overall percentage of correctly classified pixels.

The choice of evaluation metric is crucial, as different metrics may emphasize different aspects of segmentation performance. For instance, the Dice coefficient is particularly sensitive to boundary accuracy, while IoU may be more robust to variations in segmentation size. The selection of appropriate metrics should be guided by the specific requirements of the segmentation task and the characteristics of the dataset.

Benchmark datasets play a crucial role in evaluating and comparing different U-Net variants. Popular datasets include BraTS [23], [32], which contains brain tumor MRI images, Data Science Bowl [9], [19], which includes lung cancer images, CVC-ClinicDB [9], [19], which contains colon polyp images, and ISIC [3], [19], [33], which contains skin lesion images. These datasets provide a standardized platform for comparing the performance of different models, allowing researchers to assess the relative strengths and weaknesses of various U-Net architectures across different tasks and imaging modalities [34]. The availability of these publicly accessible datasets has significantly contributed to the rapid advancement of U-Net-based medical image segmentation.

6. Challenges and Future Directions

Despite the remarkable success of U-Net in medical image segmentation, several challenges remain. Addressing these challenges will be crucial for further advancing the field and realizing the full potential of U-Net in clinical practice.

6.1. Handling Imbalanced Datasets

Many medical image datasets suffer from class imbalance, where certain classes are significantly under-represented compared to others. This imbalance can lead to biased models that perform poorly on minority classes, a critical issue in medical applications where accurate detection of rare events is often crucial [2], [21]. Developing robust U-Net variants that can effectively handle imbalanced datasets remains a significant challenge. Strategies such as data augmentation, cost-sensitive learning, and the use of specialized loss functions, like the ones mentioned earlier, are promising avenues for addressing this issue [2], [21].

6.2. Improving Computational Efficiency

The computational demands of some U-Net variants, particularly those incorporating transformers, can be high, limiting their applicability in resource-constrained environments, such as point-of-care settings or mobile devices [35]. Developing more computationally efficient architectures is essential for broader clinical adoption. Lightweight U-Nets, such as DSCA-Net [36] and Half-UNet [18], represent promising efforts in this direction, demonstrating that significant reductions in model size and computational cost can be achieved without substantial loss of segmentation accuracy [36], [18]. Efficient implementations on edge devices, like the one presented in EdgeMedNet [35], are crucial for making U-Net-based solutions more accessible and practical [35].

6.3. Addressing Data Scarcity

Acquiring large, well-annotated medical image datasets is often expensive and time-consuming, posing a significant barrier to the development and evaluation of U-Net models. Developing U-Net variants that can perform well with limited data is crucial for expanding their applicability to less-studied diseases or specific patient populations [26]. Techniques such as transfer learning, where pre-trained models are fine-tuned on smaller datasets, and data augmentation, where existing data is artificially expanded, can help to mitigate the effects of data scarcity [26]. Furthermore, techniques like self-supervised learning are emerging as potential solutions to reduce the reliance on large labelled datasets [26].

6.4. Enhancing Generalizability

Many U-Net variants demonstrate excellent performance on the datasets they are trained on but struggle to generalize to new, unseen data. This lack of generalizability limits their clinical utility, as the performance of a model in a real-world setting may differ significantly from its performance on a training dataset. Improving the generalizability of U-Net models is a key area for future research. Strategies such as domain adaptation, adversarial training, and the use of more robust feature representations are likely to play a significant role in enhancing the generalizability of U-Net models.

6.5. Integrating Explainability and Interpretability

The "black box" nature of deep learning models, including U-Net, can hinder their adoption in clinical settings where transparency and understanding are critical. Developing more explainable and interpretable U-Net variants is crucial for building trust and facilitating clinical adoption. Techniques such as attention visualization, saliency maps, and the use of simpler, more interpretable architectures can help to improve the transparency and interpretability of U-Net models. This will allow clinicians to better understand the model's decision-making process, increasing confidence in its predictions and facilitating more informed clinical decisions.

7. Conclusion: The Ongoing Evolution of U-Net in Medical Imaging

U-Net has revolutionized medical image segmentation, providing a powerful and versatile framework for a wide range of clinical tasks. The numerous architectural modifications reviewed in this paper highlight the ongoing efforts to improve its performance, efficiency, and applicability. While significant progress has been made, several challenges remain, including handling imbalanced datasets, improving computational efficiency, addressing data scarcity, enhancing generalizability, and integrating explainability. Future research will likely focus on addressing these challenges to further advance the role of U-Net in medical image processing and computer-aided diagnosis. The continued development and refinement of U-Net and its variants will undoubtedly play a significant role in improving healthcare, facilitating earlier and more accurate diagnosis, and enabling more personalized and effective treatment strategies.

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1. Siddique, N., Paheding, Sidike, Elkin, Colin P., and Devabhaktuni, V.. 2020. "U-Net and Its Variants for Medical Image Segmentation: A Review of Theory and Applications". IEEE Access. https://doi.org/10.1109/ACCESS.2021.3086020

2. Zhao, Wenshuai and Zeng, Zengfeng. 2019. "Multi Scale Supervised 3D U-Net for Kidney and Tumor Segmentation". None. https://doi.org/10.24926/548719.007

3. Siddique, N., Paheding, Sidike, Angulo, Abel A. Reyes, Alom, Md. Zahangir, and Devabhaktuni, V.. 2022. "Fractal, recurrent, and dense U-Net architectures with EfficientNet encoder for medical image segmentation". Journal of Medical Imaging. https://doi.org/10.1117/1.JMI.9.6.064004

4. Zhou, Zongwei, Siddiquee, Md Mahfuzur Rahman, Tajbakhsh, Nima, and Liang, Jianming. 2019. "UNet++: Redesigning Skip Connections to Exploit Multiscale Features in Image Segmentation". Institute of Electrical and Electronics Engineers. https://doi.org/10.1109/tmi.2019.2959609

5. Peng, Yao, Sonka, Milan, and Chen, D. Z.. 2023. "U-Net v2: Rethinking the Skip Connections of U-Net for Medical Image Segmentation". arXiv.org. https://doi.org/10.48550/arXiv.2311.17791

6. Fan, Tongle, Wang, Guanglei, Li, Yan, and Wang, Hongrui. 2020. "MA-Net: A Multi-Scale Attention Network for Liver and Tumor Segmentation". Institute of Electrical and Electronics Engineers. https://doi.org/10.1109/access.2020.3025372

7. Zhong, Qiyong, et al.. 2022. "Performance Comparison between U-Net Variant

Models in Spine Segmentation". International Conference on Universal Village. https://doi.org/10.1109/UV56588.2022.10185445

8. Khanh, Trinh Le Ba, Dao, Duy-Phuong, Ho, Ngoc-Huynh, Yang, Hyung-Jeong, Baek, EuTteum, Lee, Guee-Sang, Kim, Soo-Hyung, and Yoo, Seok Bong. 2020. "Enhancing U-Net with Spatial-Channel Attention Gate for Abnormal Tissue Segmentation in Medical Imaging". Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/app10175729

9. Xiang, Sihao and Liu, Peng. 2023. "GAM-UNet: incorporating global attention mechanism into U-Net for improved medical image segmentation". None. https://doi.org/10.1117/12.2681192

10. Zhang, Nanxing, Ma, Shiqiang, Li, Xia, Zhang, Jiahui, Tang, Jijun, and Guo, Fei. 2022. "Multi-scale Neighborhood Attention Transformer on U-Net for Medical Image Segmentation". IEEE International Conference on Bioinformatics and Biomedicine. https://doi.org/10.1109/BIBM55620.2022.9994872

11. Alom, Md. Zahangir, Yakopcic, C., Hasan, Mahmudul, Taha, T., and Asari, V.. 2019. "Recurrent residual U-Net for medical image segmentation". Journal of Medical Imaging. https://doi.org/10.1117/1.JMI.6.1.014006

12. Li, Zan, Zhang, Hong, Li, Zheng-Guang, and Ren, Zuyue. 2022. "Residual-Attention UNet++: A Nested Residual-Attention U-Net for Medical Image Segmentation". Applied Sciences. https://doi.org/10.3390/app12147149

13. Zhuang, Juntang. 2018. "LadderNet: Multi-path networks based on U-Net for medical image segmentation". Cornell University. https://doi.org/10.48550/arxiv.1810.07810

14. Chen, Jieneng, Lu, Yongyi, Yu, Qihang, Luo, Xiangde, Adeli, E., Wang, Yan, Lu, Le, Yuille, A., and Zhou, Yuyin. 2021. "TransUNet: Transformers Make Strong Encoders for Medical Image Segmentation". arXiv.org. https://doi.org/None

15. Lin, Ai-Jun, Chen, Bingzhi, Xu, Jiayu, Zhang, Zheng, Lu, Guangming, and Zhang, David. 2021. "DS-TransUNet: Dual Swin Transformer U-Net for Medical Image Segmentation". IEEE Transactions on Instrumentation and Measurement. https://doi.org/10.1109/tim.2022.3178991

16. Wang, Hongyi, Xie, Shiao, Lin, Lanfen, Iwamoto, Yutaro, Han, X., Chen, Yenwei, and Tong, Ruofeng. 2021. "Mixed Transformer U-Net for Medical Image Segmentation". IEEE International Conference on Acoustics, Speech, and Signal Processing. https://doi.org/10.1109/ICASSP43922.2022.9746172

17. Huang, Ziyan, Wang, Zehua, Yang, Zhikai, and Gu, Lixu. NaN. "AdwU-Net: Adaptive Depth and Width U-Net for Medical Image Segmentation by Differentiable Neural Architecture Search". International Conference on Medical Imaging with Deep

Learning. https://doi.org/None

18. Lu, Haoran, She, Yifei, Tie, Jun, and Xu, Shengzhou. 2022. "Half-UNet: A Simplified U-Net Architecture for Medical Image Segmentation". Frontiers in Neuroinformatics. https://doi.org/10.3389/fninf.2022.911679

19. Deb, Sagar Deep and Jha, R. K.. 2023. "Modified Double U-Net Architecture for Medical Image Segmentation". IEEE Transactions on Radiation and Plasma Medical Sciences. https://doi.org/10.1109/TRPMS.2022.3221471

20. Gammoudi, Islem, Ghozi, R., and Mahjoub, M.. 2022. "HDFU-Net: An Improved Version of U-Net using a Hybrid Dice Focal Loss Function for Multi-modal Brain Tumor Image Segmentation". International Conference on Cyberworlds. https://doi.org/10.1109/CW55638.2022.00019

21. Zhao, Wenshuai and Zeng, Zengfeng. 2019. "Multi Scale Supervised 3D U-Net for Kidney and Tumor Segmentation". Cornell University. https://doi.org/10.48550/arxiv.1908.03204

22. Hussain, Tahir and Shouno, Hayaru. NaN. "MAGRes-UNet: Improved Medical Image Segmentation Through a Deep Learning Paradigm of Multi-Attention Gated Residual U-Net". IEEE Access. https://doi.org/10.1109/ACCESS.2024.3374108

23. Wisaeng, Kittipol. 2023. "U-Net++DSM: Improved U-Net++ for Brain Tumor Segmentation With Deep Supervision Mechanism". Institute of Electrical and Electronics Engineers. https://doi.org/10.1109/access.2023.3331025

24. Chen, Xuanyi, Han, Zhenqi, and Lu, Yuchen. 2023. "Brain Tumor Segmentation Leveraging Optimized U-net Models". None. https://doi.org/10.1109/ICIPCA59209.2023.10257754

25. Wu, Bingxuan, Zhang, Fan, Xu, Liang, Shen, Shuwei, Shao, Pengfei, Sun, Mingzhai, Liu, Peng, Yao, Peng, and Xu, Ronald X.. 2023. "Modality preserving U-Net for segmentation of multimodal medical images". Quantitative Imaging in Medicine and Surgery. https://doi.org/10.21037/qims-22-1367

26. Ali, Owais, Ali, Hazrat, Shah, S. A. A., and Shahzad, A.. 2022. "Implementation of a Modified U-Net for Medical Image Segmentation on Edge Devices". None. https://doi.org/10.1109/TCSII.2022.3181132

27. Wang, Yun, Wei, Chang, Wang, Zhidong, Lu, Q., and Wang, Cheng-Gang. 2018. "A More Streamlined U-net for Nerve Segmentation in Ultrasound Images". ACM Cloud and Autonomic Computing Conference. https://doi.org/10.1109/CAC.2018.8623052

28. Zannah, Rafiatul, Bashar, Mubtasim, Mushfiq, Rahil Bin, Chakrabarty, Amitabha, Hossain, Shahriar, and Jung, Yong Ju. NaN. "Semantic Segmentation on Panoramic Dental X-Ray Images Using U-Net Architectures". IEEE Access.

https://doi.org/10.1109/ACCESS.2024.3380027

29. Zannah, Raatul, Bashar, Mubtasim, Chakrabarty, Amitabha, Jung, Yong Ju, Zannah, Rafiatul, Mushq, Rahil Bin, and Hossain, Shahriar. NaN. "Semantic Segmentation on Panoramic X-ray Images with U-net Architectures". None. https://doi.org/None

30. Kim, Sewon, Bae, Won C., Masuda, Koichi, Chung, Christine B., and Hwang, Dosik. 2018. "Fine-Grain Segmentation of the Intervertebral Discs from MR Spine Images Using Deep Convolutional Neural Networks: BSU-Net". Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/app8091656

31. Fajri, Fathorazi Nur, Dzikrillah, Mohammad, and Khairi, Ahmad. 2024. "Digital Fish Image Segmentation Using U-Net for Shape Feature Extraction". JURNAL TEKNOLOGI DAN OPEN SOURCE. https://doi.org/10.36378/jtos.v7i2.3968

32. Yousef, Rammah, Khan, Shakir, Gupta, Gaurav, Siddiqui, Tamanna, Albahlal, Bader M., Alajlan, Saad Abdullah, and Haq, Mohd Anul. 2023. "U-Net-Based Models towards Optimal MR Brain Image Segmentation". Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/diagnostics13091624

33. Saadati, Davoud, Manzari, Omid Nejati, and Mirzakuchaki, S.. 2023. "Dilated-UNet: A Fast and Accurate Medical Image Segmentation Approach using a Dilated Transformer and U-Net Architecture". arXiv.org. https://doi.org/10.48550/arXiv.2304.11450

34. Komosar, Aleksa, Stefanovi, Darko, and Sladojevi, Sran. NaN. "An overview of image processing in biomedicine using U-Net convolutional neural network architecture". None. https://doi.org/10.5937/jcfs3-48848

35. Liu, Qingliang, Zhou, Shuai, and Lai, Jinmei. 2023. "EdgeMedNet: Lightweight and Accurate U-Net for Implementing Efficient Medical Image Segmentation on Edge Devices". None. https://doi.org/10.1109/TCSII.2023.3291168

36. Shan, Tong, Yan, Jiayong, Cui, Xiaoyao, and Xie, Lijian. 2022. "DSCA-Net: A depthwise separable convolutional neural network with attention mechanism for medical image segmentation". Arizona State University. https://doi.org/10.3934/mbe.2023017