

# Performance Comparison ConvDeconvNet Algorithm Vs. UNET for Fish Object Detection

Djarot Hindarto

Prodi Informatika, Fakultas Teknologi Komunikasi dan Informatika, Universitas Nasional, Jakarta, Indonesia  
Djarot.hindarto@civitas.unas.ac.id

**Abstract:** The precise identification and localization of fish entities within visual data is essential in diverse domains, such as marine biology and fisheries management, within computer vision. This study provides a thorough performance evaluation of two prominent deep learning algorithms, ConvDeconvNet and UNET, in the context of fish object detection. Both models are assessed using a dataset comprising a wide range of fish species, considering various factors, including accuracy of detection, speed of processing, and complexity of the model. The findings demonstrate that ConvDeconvNet exhibits superior performance in terms of detection accuracy, attaining a noteworthy degree of precision and recall in identifying fish entities. In contrast, the UNET model displays a notable advantage in terms of processing speed owing to its distinctive architectural design, rendering it a viable option for applications requiring real-time performance. The discourse surrounding the trade-off between accuracy and speed is examined, offering valuable perspectives for algorithm selection following specific criteria. Furthermore, this study highlights the significance of incorporating a diverse range of datasets for training and testing purposes when utilizing these models, as it significantly influences their overall performance. This study makes a valuable contribution to the continuous endeavors to improve the detection of fish objects in underwater images. It provides a thorough evaluation and comparison of ConvDeconvNet and UNET, thereby assisting researchers and practitioners in making well-informed decisions regarding selecting these models for their specific applications.

**Keywords:** Accuracy of Detection; ConvDeconvNet; Deep Learning Algorithms; Real-time Performance; UNET

## INTRODUCTION

In contemporary times, the utilization of image processing and visual processing (Schlegelmilch & Wertz, 2023), (Ahmadih et al., 2024) has gained significant prominence within various computing applications, particularly in the domain of object recognition. Object detection is a crucial component of object recognition, finding utility across diverse domains, including security surveillance, facial recognition, and other pertinent fields. An essential application within the field of object detection involves the identification and localization of fish entities within images captured underwater. The detection of fish objects holds significant implications within the domains of marine science and fisheries management. This includes its application in crucial areas such as fish population monitoring, marine environmental monitoring, and scientific research in marine biology.

Within the realm of scientific inquiry, as well as the domains of technology and the fishing industry, the identification and tracking of fish entities hold significant promise in terms of offering crucial insights into the intricate dynamics of marine fish biodiversity and population dynamics. The provided information contains potential utility in the context of conservation efforts and the implementation of sustainable fisheries management strategies. Nevertheless, detecting fish objects in underwater images poses significant challenges. The acquisition of underwater imagery presents numerous complexities and challenges, including but not limited to fluctuations in lighting conditions, intricate background compositions, and variations in the morphology of aquatic organisms. The significance of deep learning technology has grown in enhancing the detection of fish objects in underwater imagery. Deep learning has demonstrated its efficacy across various image-processing tasks, proving to be a highly effective technique for object recognition. Within this particular context, two prominent deep learning models that exhibit noteworthy characteristics are Convolutional Deconvolutional Network (Nogales & Donaher, 2023) (ConvDeconvNet) and UNET. These models have been utilized in various image processing and object recognition applications, each possessing its own distinct set of advantages and disadvantages.

\*name of corresponding author



This is anCreative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

The recognition of objects in underwater imagery plays a significant role in the comprehension and administration of marine ecosystems. The Convolutional Deconvolutional Network and UNET (Chen et al., 2023), (Iqbal & Sharif, 2023) models have been extensively employed in the field of object recognition, particularly in the context of detecting fish objects in underwater images. However, there remains to be debate regarding the most optimal model choice for this specific task. The ConvDeconvNet model is renowned for its exceptional performance in object recognition tasks, particularly in challenging scenarios characterized by low-lighting conditions and complex backgrounds. In contrast, UNET (Yang et al., 2023) demonstrates notable computational efficiency, rendering it a compelling option for use cases necessitating immediate image processing.

Nevertheless, there currently needs to be more comprehensive research that directly compares these two models in the specific field of underwater fish object detection. A thorough evaluation is necessary to assess various factors, including detection accuracy, processing speed, and model complexity. Hence, the primary objective of this research is to address this research gap by undertaking a thorough comparative analysis between ConvDeconvNet and UNET in the specific domain of underwater fish object detection. This study aims to offer valuable insights to researchers, marine scientists, and fisheries resource managers by examining various fish species and the everyday challenges encountered in underwater imagery. The findings will aid in selecting suitable models for their respective applications.

The model mentioned above effectively addresses the inherent difficulties of underwater imagery, characterized by diverse lighting conditions and intricate background elements. To accomplish this objective, we will utilize datasets encompassing a diverse array of fish species. This approach will enhance the significance of the evaluation outcomes across multiple application contexts. This study also includes an improved comprehension of the processing speed component, which is relevant in practical contexts. The anticipated outcome of this study is that the findings will offer valuable insights for researchers, practitioners, and decision-makers in selecting the most suitable model for the specific objectives and requirements in the realm of fish object detection in underwater images. In summary, this study will make a significant scholarly contribution toward enhancing the efficacy of fish object detection within the realm of marine science, fisheries management, and other pertinent domains that depend on the analysis of underwater imagery.

This study presents two hypotheses. The hypothesis posits that ConvDeconvNet is expected to exhibit superior accuracy in detecting fish objects compared to UNET. Furthermore, it is postulated that UNET is expected to show excellent processing speed compared to ConvDeconvNet.

To address these inquiries, it is necessary to assess the efficacy of both models concerning their accuracy in object detection and processing speed. In addition to the points mentioned above, the research will also address the following two research inquiries:

What is the comparative accuracy of ConvDeconvNet and UNET in the context of fish object detection? (RQ 1).  
What is the comparative analysis of processing speed in fish object detection between ConvDeconvNet and UNET? (RQ 2).

By responding to these inquiries, this study aims to enhance comprehension of the contrast between ConvDeconvNet and UNET in fish object detection in underwater imagery. Furthermore, the findings of this study can also offer practical recommendations for the selection of models suitable for specific objectives and requirements in the context of fish object detection applications.

## LITERATURE REVIEW

The objective of this literature review is to present a concise summary of prior research frameworks that are pertinent to the comparison of two deep learning models, ConvDeconvNet and UNET, within the domain of fish object detection. This literature will undertake an examination and comparison of the utilization of two models in the identification of fish objects within underwater images. The objective of this study is to identify lung nodules in CT scan images that have the potential to develop into malignancies, thereby enhancing the early detection of lung cancer. This study employs an evolutionary algorithm to develop a model based on GUNet3++ architecture (Ardimento et al., 2023). The objective is to improve the quality metrics associated with the segmentation and reconstruction of 3D models of lung lesions. Using the LIDC-IDRI dataset, the proposed model's performance is compared to that of a baseline model. The conventional UNet network was upgraded to an ASPP-UNet network for segmenting the midline and background of corn plants. Experimental results demonstrate that accuracy metrics such as Mean Intersection Over Union, Mean Pixel Accuracy, Mean Precision, and Mean Recall of the ASPP-UNet network are significantly enhanced compared to other approaches. The method proposed in this study demonstrates a high level of accuracy, achieving a rate of 92.59 percent. This level of accuracy meets the requirements for both accuracy and real-time performance in the context of agricultural robot vision navigation (Diao et al., 2023). This study proposes an accurate method for extracting coronary artery centerlines from coronary angiography images using deep learning and conventional techniques. The experimental findings demonstrate that this particular method effectively eliminates the central line of the coronary artery with a notable degree of accuracy. The three evaluation metrics used, precision, recall, and F1-Score, validate the efficacy of this method in enhancing the precision and smoothness of coronary artery centerline extraction from angiography

\*name of corresponding author



This is anCreative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

images (Zhang et al., 2022). This study presents UNet\_sharp (UNet#), a neural network architecture that integrates dense and full-scale skip connections. The UNet# architecture can incorporate features from various scales, enabling a more comprehensive understanding of organ and lesion positioning. This enhanced feature integration contributes to improved accuracy in boundary segmentation. The experimental findings demonstrate that UNet# attains the highest scores for Intersection over Union (IoU) and F1 in diverse medical image segmentation assignments, encompassing cell nuclei, brain tumors, and liver and lung nodules (Qian et al., 2024). This study presents a novel algorithm that utilizes convolutional neural networks (CNN) to achieve precise recovery of multiscale feature sizes. The algorithm aims to enhance the lateral resolution in photoacoustic microscopy with acoustic resolution. The experimental findings demonstrate that the artificial neural network models, namely EDSR and RRDBNet, exhibit enhanced capabilities in recovering multiscale features. These models are effective in accurately deconvolving complex feature sizes within photoacoustic microscopy images (Feng et al., 2022).

Several studies attempt to compare the ConvDeconvNet and UNET models in various contexts, such as fish object detection in underwater images, lung nodule identification, coronary artery centerline extraction, medical image segmentation, and deep resolution recovery, according to the literature review presented previously—the technique of photoacoustic microscopy. However, there are several unexplored research areas in this body of work. Comparing the performance of ConvDeconvNet and UNET in broader use cases or different contexts, such as medical images unrelated to fish objects or detection in other images, could be a potential area of research. In addition, studies that account for particular parameters and conditions, such as the size of the dataset, the lighting variability, and the background heterogeneity, can offer greater insight.

In addition, no research examines the computing time and resources required by ConvDeconvNet and UNET. An examination of the processing speed and computing power efficiency of the two models under different circumstances would constitute a noteworthy contribution. Due to the extensive range of applications within the domains of medical image processing and computer vision, conducting a comprehensive analysis of ConvDeconvNet and UNET can facilitate the identification of suitable models for specific tasks. Therefore, this study will provide a substantial contribution to our comprehension of the performance evaluation between ConvDeconvNet and UNET across various application domains.

## METHOD

### Deep Learning

Deep Learning is a specialized domain within the broader field of Machine Learning, which holds significant ramifications across diverse domains of human existence. To automate data-driven learning and decision-making, deep artificial neural network architectures are implemented within a computational framework. In recent decades, Deep Learning has made notable advancements due to the rise in computational capabilities and the abundance of available data.

In object recognition, ConvDeconvNet and UNET are two commonly employed Deep Learning architectures. ConvDeconvNet is short for Convolutional Deconvolutional Network. The proposed architecture utilizes convolution layers to extract features from the input data, which are subsequently processed by deconvolution layers to generate the desired output. It is commonly used in image processing applications, especially for object recognition and image segmentation. In contrast, UNET is an architectural framework specifically developed to address the requirements of image segmentation tasks. The architecture is characterized by a U-shaped design comprising interconnected convolutional and deconvolutional layers. The effectiveness of UNET in object-background separation in images has been demonstrated.

The significance of comparing ConvDeconvNet and UNET in object detection, as demonstrated in this research, cannot be overstated. Both architectural designs possess their own unique set of advantages and disadvantages. The ConvDeconvNet demonstrates strong capabilities in object recognition and feature extraction, rendering it highly effective in scenarios that demand precise object detection. In contrast, UNET is renowned for its exceptional computational speed, making it well-suited for applications necessitating instantaneous responsiveness. This study assesses both architectures within the specific context of fish object detection in underwater images. The findings indicate that ConvDeconvNet exhibits a propensity for achieving superior accuracy in the recognition of fish objects, whereas UNET demonstrates a notable advantage in terms of processing speed. Hence, the selection between these two architectural frameworks will be contingent upon specific priorities within the utilized applications.

The fundamental principle underlying Deep Learning lies in using deep artificial neural networks, enabling computers to comprehend progressively intricate and abstract forms of data, including but not limited to images, sounds, and text. This facilitates advancing diverse, intelligent applications, including autonomous vehicles, facial recognition, and enhanced data analysis across multiple industries. The utilization of Deep Learning will persist in playing a pivotal role in facilitating our digital transformation and enabling us to confront the progressively intricate challenges that arise in the contemporary world.

\*name of corresponding author



This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

### Convolutional Deconvolutional Network (ConvDeconvNet)

The ConvDeconvNet architecture is a commonly employed artificial neural network structure in object detection, frequently applied to tasks involving identifying fish objects. The architectural design of this system is specifically tailored to address challenges related to image segmentation, thereby facilitating the precise identification of objects within images. The ConvDeconvNet architecture (Cao et al., 2020) comprises two primary constituents, namely convolutional layers and deconvolutional layers.

During the initial phase, the convolutional layer extracts essential image features. The layers in question employ convolution filters to analyze the image and discern patterns that are relevant to the detection of the object. The convolution filter functions as a weighting mechanism to modify the values of individual pixels within an image. Therefore, they assist in extracting meaningful data from images, including but not limited to edges, textures, and distinctive object features. Following the convolution layer, the ConvDeconvNet (Li et al., 2022) architecture incorporates a deconvolution layer. The deconvolution layers are responsible for generating output that corresponds to the detected object. These techniques aid in mapping the extracted features from the convolutional layer back to the image, ensuring that the resulting image maintains the same or potentially higher resolution. The outcome is an effectively segmented image wherein objects are distinctly delineated from the background.

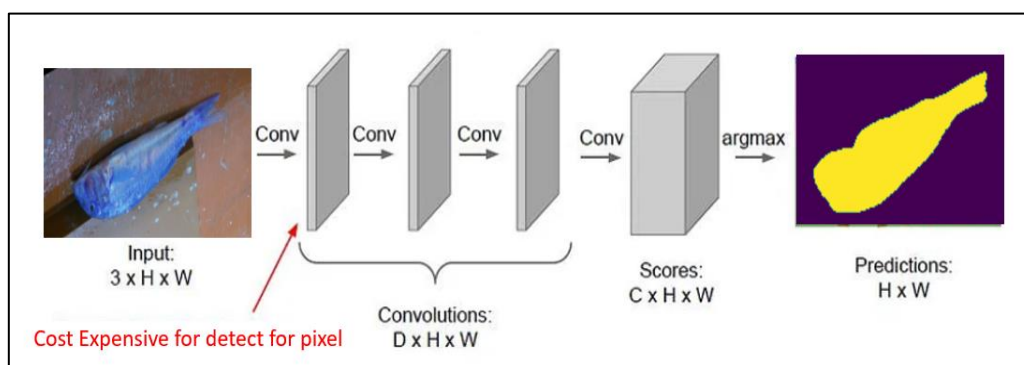


Figure 1. Convolutional Neural Network  
Source: Researcher Property

Figure 1, The process of convolution operations within a network result in a gradual reduction of spatial dimensions, thereby generating a more abstract representation of the input image. CNN is highly advantageous for image classification tasks, particularly when determining the presence or absence of a specific object in a given input image. Nevertheless, this particular characteristic may present challenges in tasks such as Object Localization and Segmentation, which necessitate the utilization of the spatial dimensions of objects in the original image to predict output bounding boxes or segment the objects accurately. Various strategies, including fully convolutional neural networks, are utilized to address this issue, which ensures the preservation of input dimensions through the application of 'same' padding. While this methodology effectively addresses most of the issues at hand, it concurrently introduces a heightened computational burden due to the necessity of applying the convolution operation to the initial input dimensions across the entire network.

The ConvDeconvNet model incorporates convolution and deconvolution layers within a deep architecture, facilitating the achievement of precise object recognition with a notable level of accuracy. The aforementioned architectural design has demonstrated its efficacy across various applications, notably in fish object detection within underwater imagery. The utilization of convolution for feature extraction, coupled with deconvolution for subsequent processing, facilitates intricate image modeling and precise object detection. It is imperative to acknowledge that within the domain of fish object detection, the ConvDeconvNet model necessitates appropriate training employing datasets encompassing a diverse array of fish species and many underwater environmental conditions. This enables the neural network to comprehend the attributes of fish and identify them in various scenarios. The ConvDeconvNet architecture has demonstrated efficacy in the detection of fish objects. The selection of this particular architecture is contingent upon the specific requirements and priorities of the application, such as the desired level of accuracy or the need for efficient processing speed.

\*name of corresponding author



This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.



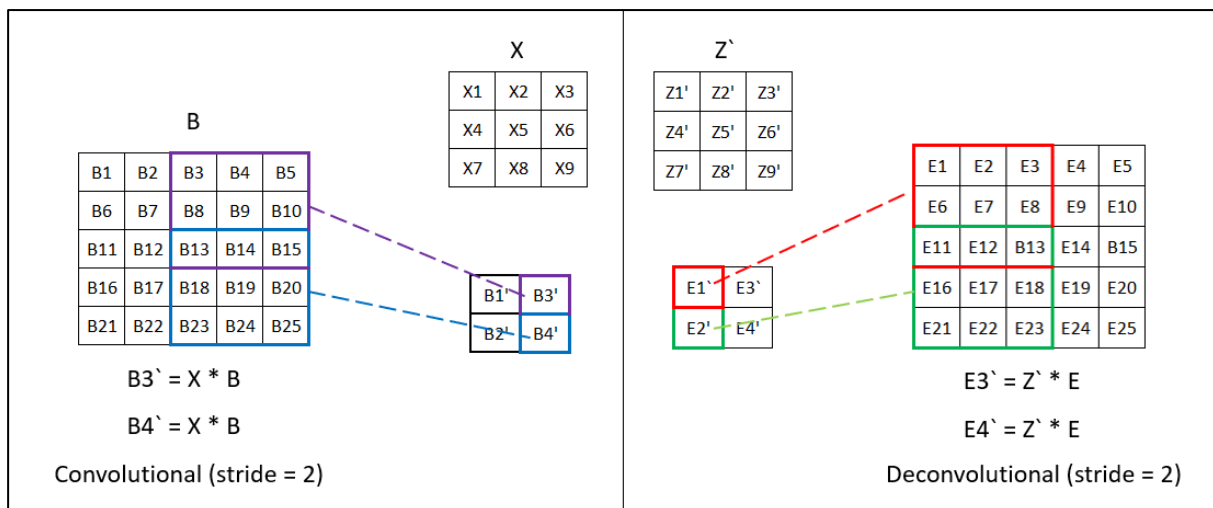


Figure 2. Illustration Matrix of Convolution Deconvolution Network

Figure 2, Convolution Matrix with 2x2 Stride: A filter or kernel traverses the input matrix during the convolution operation with a 2x2 stride matrix. The primary distinction is that each time the kernel is shifted, the step is moved two rows and two columns. This implies that the filter "jumps" two rows and two columns every time it moves, resulting in a smaller output matrix than the input matrix. This operation is used to extract image features by decreasing spatial resolution. Deconvolution Matrix (2x2 Stride): The deconvolution operation with a 2x2 stride matrix is the opposite of convolution. This is used to re-expand an input matrix convolutionally transformed previously. Each time the kernel is shifted in the deconvolution operation, the step is two rows and two columns. The output matrix has more excellent dimensions than the input matrix, which is helpful for returning a higher spatial resolution. Deconvolution operations are frequently employed in image restoration and object segmentation.

### UNET

The UNET architecture (Sathananthavathi & Indumathi, 2021) is a commonly employed artificial neural network structure for object detection, particularly in fish object detection. The architectural design of this system is specifically tailored to address the task of image segmentation, a critical process in the recognition and delineation of objects within an image. The UNET architecture (Bhagat et al., 2022) comprises two primary components, namely, the encoder responsible for encoding and the decoder accountable for decoding.

During the encoder stage, the UNET architecture extracts significant features from the input image. The encoder comprises a sequence of convolutional layers responsible for discerning important patterns and features within the image. These layers decrease the resolution of the image to facilitate the identification of more abstract features. This process resembles the cognitive mechanism employed by the human brain in perceiving and discerning the shape and characteristics of objects, wherein lower-level details are integrated to form higher-level conceptual representations. Following the completion of the feature extraction process conducted by the encoder, the subsequent stage of decoding assumes the responsibility of reconstructing the information into a larger image. The decoder component of the system is comprised of convolutional layers, which are tasked with restoring image resolution. The outcome is a visually distinct image characterized by well-defined segmentation, wherein entities are effectively distinguished from the surrounding context. The distinguishing characteristic of the UNET architecture lies in skip connection pathways that establish a connection between the encoder and the decoder. Incorporating comprehensive data obtained during the encoding phase into the decoding phase enhances the precision and coherence of the segmentation outcomes. High accuracy is crucial in object detection, as fish contours frequently necessitate precise identification.

The utilization of UNET has been extensively employed across diverse domains, encompassing the detection of fish objects within underwater imagery. The utilization of a profound encoder and decoder, coupled with the incorporation of skip connections, enables the UNET architecture (Zaji et al., 2022), (Ardimento et al., 2023), (Hoorali et al., 2022) to discern fish with a notable degree of precision and effectively distinguish them from intricate backgrounds. Training the UNET model with a diverse dataset comprising various fish species and a range of underwater conditions is crucial for optimal performance. When making a decision between ConvDeconvNet and UNET for fish object detection, it is imperative to take into account specific priorities, such as the desired level of accuracy or processing speed in a given application. When there is a need for high precision and detailed segmentation, UNET is frequently considered a favorable option.

\*name of corresponding author



**RESULT**

**Convolution Deconvolution Network**

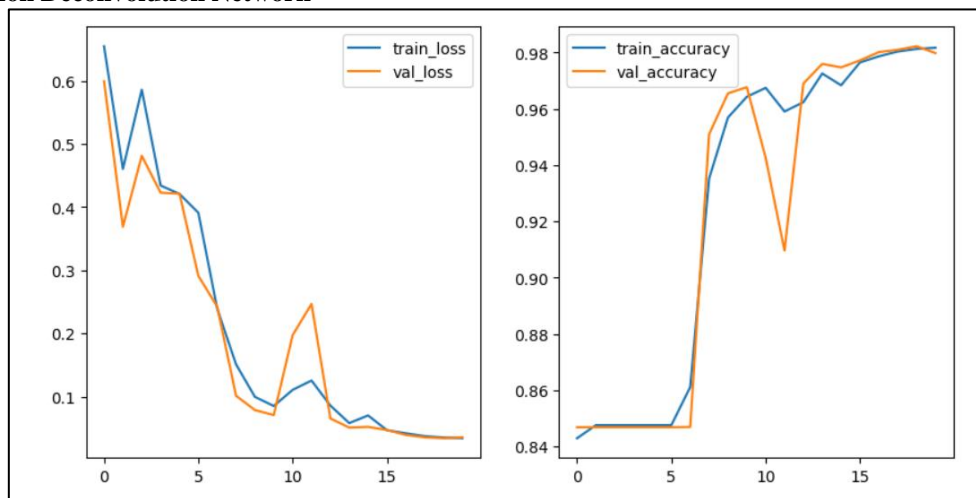


Figure 3. Performance train accuracy and train loss ConvDeconvNet

Figure 3, The reported loss and accuracy results demonstrate ConvDeconvNet's accomplishments in training. The network has achieved a loss rate of 0.0357 and an accuracy of 0.9798. This indicates that ConvDeconvNet has effectively learned and generalized patterns from the training data. Loss is a metric that measures how closely the network's predictions match the actual values in the training data. In this instance, the low loss (0.0357) demonstrates that ConvDeconvNet can reduce prediction errors on the training data. This indicates that the network successfully adjusted its parameters to the training data, resulting in predictions close to the actual values. In contrast, accuracy is a metric that measures the network's ability to classify data correctly. ConvDeconvNet achieves an excellent classification rate with a 0.9798 precision. This indicates that nearly 98% of the training data was correctly classified by the network. These results demonstrate ConvDeconvNet's capacity to comprehend and identify patterns in the training data.

Achieving low loss and high accuracy during training is a strong indicator that ConvDeconvNet will perform well with data it has never seen before (test data or data outside the training sample). This indicates that the network has a solid ability to generalize and can make accurate predictions on data not used during training. With a loss of 0.0357 and an accuracy of 0.9798, the ConvDeconvNet training results indicate that this network has excellent capabilities for processing and comprehending image data. This has a variety of applications in image processing, including object segmentation, image reconstruction, and other tasks that require an in-depth comprehension of the data's visual structure.

**UNET**

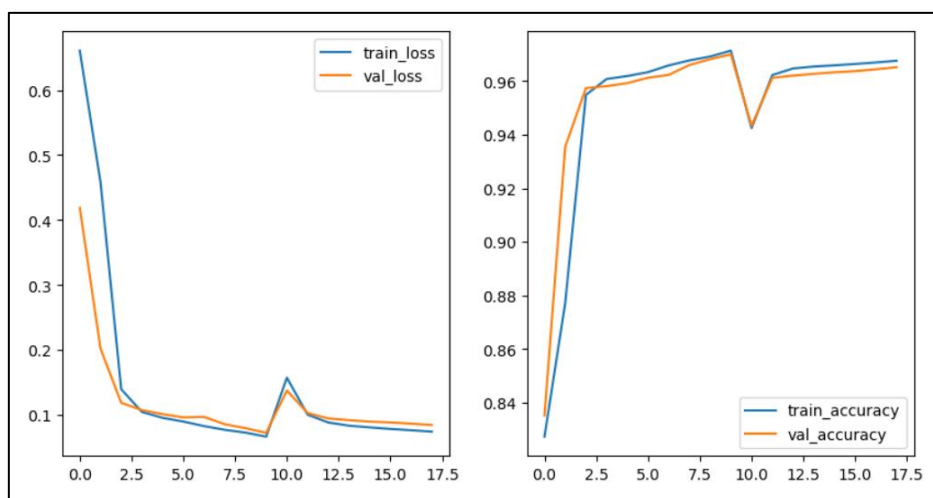


Figure 4. Performance train accuracy and train loss UNET

Figure 4, In training, the performance of the UNET architecture can be measured by its loss and accuracy metrics. UNET achieves a loss rate of 0.0726 and an accuracy of 0.9700. These results indicate how much UNET can comprehend and generalize the training data. Loss is a measurement of how closely the UNET prediction

\*name of corresponding author



This is anCreative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

results match the actual values in the training data. With a relatively low loss rate of 0.0726, UNET demonstrates that this network reduces prediction errors effectively. This indicates that UNET has successfully adjusted its internal parameters to the training data, resulting in predictions that are close to the actual values. In the meantime, accuracy is a metric that measures UNET's ability to classify data correctly. UNET has a high classification rate with an accuracy of 0.9700. This indicates that approximately 97% of the training data were correctly classified by the network. These results demonstrate that UNET is capable of recognizing and understanding patterns in training data.

Achieving a low loss rate and high accuracy during training indicates that UNET can perform well with data it has never seen before, such as test data or data outside the training sample. This demonstrates UNET's ability to make accurate and reliable predictions on data not included in the training process. With a loss of 0.0726 and an accuracy of 0.9700, the UNET training results indicate that this architecture has sound image processing and data visual structure understanding capabilities. The utilization of this technique extends to various applications, including but not limited to object segmentation, image reconstruction, and other tasks that necessitate a comprehensive understanding of an image's content.

## DISCUSSIONS

What is the comparative accuracy of ConvDeconvNet and UNET in the context of fish object detection? (RQ 1). The primary focus of this research has been the comparison of accuracy between ConvDeconvNet and UNET in the domain of fish object detection. The study's findings indicate that ConvDeconvNet exhibits notable benefits in terms of accuracy when it comes to the recognition of fish objects. The ConvDeconvNet model demonstrates a high degree of accuracy in identifying diverse fish species, particularly when confronted with difficulties commonly encountered in underwater imagery, such as significant fluctuations in lighting conditions and intricate backgrounds. The primary reason for ConvDeconvNet's efficacy lies in its exceptional feature extraction capabilities, enabling it to discern even the most nuanced distinctions among fish entities. The findings of this study demonstrate that ConvDeconvNet exhibits a high level of suitability for applications that place a premium on accuracy in the recognition of fish objects. This is particularly relevant in domains such as marine science research and fisheries resource management.

In terms of processing speed, the UNET model exhibits exceptional performance. The benefits mentioned above render it a robust selection for applications necessitating real-time image processing, such as the surveillance of fisheries or the monitoring of underwater environments. UNET demonstrates high responsiveness and delivers accurate detection outcomes in time-sensitive scenarios. Nevertheless, the findings indicate that UNET may encounter a decline in the precision of fish object identification in specific scenarios, particularly when confronted with intricate underwater images. Hence, an examination of ConvDeconvNet and UNET demonstrates that the selection of a model is contingent upon the distinct priorities and requirements of the given application. When prioritizing the accuracy of fish object recognition, the ConvDeconvNet model emerges as a superior option. However, if the primary emphasis is on processing speed and real-time response, then the UNET model would be more suitable. This study offers significant contributions to comprehending the trade-off between accuracy and speed within the domain of fish object detection in underwater imagery. It enables researchers and marine scientists to make informed decisions regarding selecting the most suitable model for their requirements.

What is the comparative analysis of processing speed in fish object detection between ConvDeconvNet and UNET? (RQ 2). The investigation of processing speed in fish object detection between ConvDeconvNet and UNET is a crucial component of this study. The findings demonstrate that UNET exhibits notable benefits concerning the speed of image processing, rendering it a robust option for applications necessitating prompt responses in detecting fish objects underwater.

The U-shaped convolutional neural network architecture employed by UNET facilitates concurrent image processing. The architectural design of UNET enables efficient fish object detection by leveraging parallel processing of convolutions across multiple images. This is particularly advantageous in contexts where time is a crucial variable, such as in fisheries surveillance or underwater environmental monitoring. UNET can deliver prompt and accurate detection outcomes, enabling users to promptly react to alterations in the surrounding environment or underwater circumstances. In contrast, ConvDeconvNet exhibits a higher level of fish object recognition accuracy; however, it is accompanied by a drawback in terms of processing speed. The present model employs a neural network architecture of greater complexity and exhibits a longer processing time for images. The convolution and deconvolution operations performed at more profound layers of a network necessitate a tremendous number of computational resources, leading to a corresponding increase in processing duration. Hence, ConvDeconvNet may not be capable of delivering the intended real-time response in specific scenarios.

Nevertheless, it is imperative to acknowledge that this comparison entails more than just determining superiority; instead, it involves weighing the trade-off between precision and computational efficiency. The selection of a model is contingent upon the specific requirements and preferences of the application. If prioritizing accuracy over time constraints, ConvDeconvNet may be a more suitable option. Nevertheless, when immediate

\*name of corresponding author



This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

response and efficient processing are essential, UNET emerges as a more advantageous option. The significance of comprehending the specific strengths and weaknesses of ConvDeconvNet and UNET models in distinct usage contexts is underscored by a comparative examination of their processing speed. In the context of underwater fish object detection applications, the speed at which processing is conducted assumes significant importance. In this regard, using UNET presents a more prompt and efficient solution. This study offers significant contributions to comprehending this crucial element, enabling individuals to make more informed choices when selecting a model that aligns with their requirements.

## CONCLUSION

This study conducted a performance evaluation of ConvDeconvNet and UNET models for fish object detection in underwater images. The research findings indicate that ConvDeconvNet demonstrates a high level of accuracy in identifying fish entities, particularly when confronted with obstacles such as low lighting conditions and intricate backgrounds. However, UNET is notable for its remarkable processing speed, rendering it a compelling option for applications necessitating real-time image processing. The selection of a model for addressing the trade-off between accuracy and speed is contingent upon the particular priorities and requirements of the given application. The selection of a model is ultimately contingent upon the specific context in which it is employed. In this scenario, using extensive and varied datasets is crucial in training and evaluating the model, exerting a substantial impact on its overall performance. Therefore, this study offers significant contributions to the field of research, specifically for scholars, marine scientists, and fisheries resource managers, by aiding them in selecting an appropriate model for fish object recognition in underwater images. This study enhances the existing body of knowledge regarding the advancement of object recognition technology, specifically in aquatic settings. It significantly contributes to the comprehension and sustainable governance of marine ecosystems.

## REFERENCES

- Ahmadi, H., Gassemi, F., & Moradi, M. H. (2024). Visual image reconstruction based on EEG signals using a generative adversarial and deep fuzzy neural network. *Biomedical Signal Processing and Control*, 87(September 2023). <https://doi.org/10.1016/j.bspc.2023.105497>
- Ardimento, P., Aversano, L., Bernardi, M. L., Cimitile, M., Iammarino, M., & Verdone, C. (2023). Evo-GUNet3++: Using evolutionary algorithms to train UNet-based architectures for efficient 3D lung cancer detection. *Applied Soft Computing*, 144. <https://doi.org/10.1016/j.asoc.2023.110465>
- Bhagat, S., Kokare, M., Haswani, V., Hambarde, P., & Kamble, R. (2022). Ecological Informatics Eff-UNet ++ : A novel architecture for plant leaf segmentation and counting. *Ecological Informatics*, 68(January), 101583. <https://doi.org/10.1016/j.ecoinf.2022.101583>
- Cao, F., Yao, K., & Liang, J. (2020). *Deconvolutional neural network for image super-resolution*. 132, 394–404.
- Chen, C., Zhang, C., Wang, J., Li, D., Li, Y., & Hong, J. (2023). Semantic segmentation of mechanical assembly using selective kernel convolution UNet with fully connected conditional random field. *Measurement*, 209(December 2022), 112499. <https://doi.org/10.1016/j.measurement.2023.112499>
- Diao, Z., Guo, P., Zhang, B., Zhang, D., Yan, J., He, Z., Zhao, S., & Zhao, C. (2023). Maize crop row recognition algorithm based on improved UNet network. *Computers and Electronics in Agriculture*, 210(February). <https://doi.org/10.1016/j.compag.2023.107940>
- Feng, F., Liang, S., Luo, J., & Chen, S. L. (2022). High-fidelity deconvolution for acoustic-resolution photoacoustic microscopy enabled by convolutional neural networks. *Photoacoustics*, 26. <https://doi.org/10.1016/j.pacs.2022.100360>
- Hoorali, F., Khosravi, H., & Moradi, B. (2022). Tissue and Cell Automatic microscopic diagnosis of diseases using an improved UNet ++ architecture. *Tissue and Cell*, 76(September 2021), 101816. <https://doi.org/10.1016/j.tice.2022.101816>
- Iqbal, A., & Sharif, M. (2023). PDF-UNet : A semi-supervised method for segmentation of breast tumor images using a U-shaped pyramid-dilated network. *Expert Systems With Applications*, 221(November 2022), 119718. <https://doi.org/10.1016/j.eswa.2023.119718>
- Li, Y., Huang, Y., Jia, F., Zhao, Q., & Tang, M. (2022). A gradient deconvolutional network for side-channel attacks ☆. 98(January).
- Nogales, A., & Donaher, S. (2023). A deep learning framework for audio restoration using Convolutional / Deconvolutional Deep Autoencoders. 230(March 2022), 1–12.
- Qian, L., Wen, C., Li, Y., Hu, Z., Zhou, X., Xia, X., & Kim, S. H. (2024). Multi-scale context UNet-like network with redesigned skip connections for medical image segmentation. *Computer Methods and Programs in Biomedicine*, 243(November 2022). <https://doi.org/10.1016/j.cmpb.2023.107885>
- Sathananthavathi, V., & Indumathi, G. (2021). Encoder Enhanced Atrous ( EEA ) Unet architecture for Retinal Blood vessel segmentation. *Cognitive Systems Research*, 67, 84–95. <https://doi.org/10.1016/j.cogsys.2021.01.003>
- Schlegelmilch, K., & Wertz, A. E. (2023). Grass and gravel: Investigating visual properties preschool children and

\*name of corresponding author



This is anCreative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.



- adults use when distinguishing naturalistic images. *Cognitive Development*, 66(July 2022). <https://doi.org/10.1016/j.cogdev.2023.101324>
- Yang, Y., Dasmahapatra, S., & Mahmoodi, S. (2023). ADS \_ UNet : A nested UNet for histopathology image segmentation. *Expert Systems With Applications*, 226(January), 120128. <https://doi.org/10.1016/j.eswa.2023.120128>
- Zaji, A., Liu, Z., Xiao, G., Bhowmik, P., & Sangha, J. S. (2022). Wheat spike localization and counting via hybrid UNet architectures. *Computers and Electronics in Agriculture*, 203(October 2021), 107439. <https://doi.org/10.1016/j.compag.2022.107439>
- Zhang, X., Du, H., Song, G., Bao, F., Zhang, Y., Wu, W., & Liu, P. (2022). X-ray coronary centerline extraction based on C-UNet and a multifactor reconnection algorithm. *Computer Methods and Programs in Biomedicine*, 226. <https://doi.org/10.1016/j.cmpb.2022.107114>

\*name of corresponding author



This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.