Deep Learning for Denoising Bioluminescent Interference and Electronic Artifacts in Marine Phytoplankton Microscopy

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Abstract - *The field of phytoplankton imaging and detection has emerged as a significant area of inquiry for the past twenty-five years. This is evidenced by the abundance of datasets that contain numerous images of these microscopic organisms. However, a major challenge that hinders the progress of this field is the presence of noise in these images, which originates from two sources: the bioluminescent interference caused by the phytoplankton themselves, and the electronic noise associated with the imaging equipment. These noise types can directly impact ecological studies, due to the degrade of performance in machine learning models for classifying phytoplankton species. The aim of this research is to explore the use of a custom Convolutional Neural Network (CNN) to perform the task of image denoising. Our methodology involved training the CNN on a dataset comprising of 10,524 noisy phytoplankton images and evaluating it using standard metrics. Our model achieved a Peak Signal-to-Noise Ratio (PSNR) of 32.08 dB, followed by a Structural Similarity Index (SSIM) of 0.9788. These values are indicative of the effectiveness of our model in successfully removing undesired noise from the given images. We hope that this research serves as a starting point for further exploration and improvement.*

Key Words: *Deep learning, Noise reduction, Phytoplankton imaging, Marine Ecology, CNNs*

1.INTRODUCTION

Phytoplankton, often termed the “lungs of the ocean,” are indispensable to marine ecosystems. As primary producers, they contribute significantly to marine primary production, converting vast amounts of carbon dioxide into organic carbon through photosynthesis [1]. This process not only acts as a sink for CO2, an important factor in global carbon cycling, but also produces oxygen essential for marine and terrestrial life. Phytoplankton's role extends beyond carbon cycling. They are pivotal in other biogeochemical processes, influencing cycles of nitrogen, phosphorus, and sulphur, among others. For example, certain phytoplankton species are involved in nitrogen fixation, converting atmospheric nitrogen into a form usable by other marine organisms, thereby enriching the nutrient content of ocean waters [2].

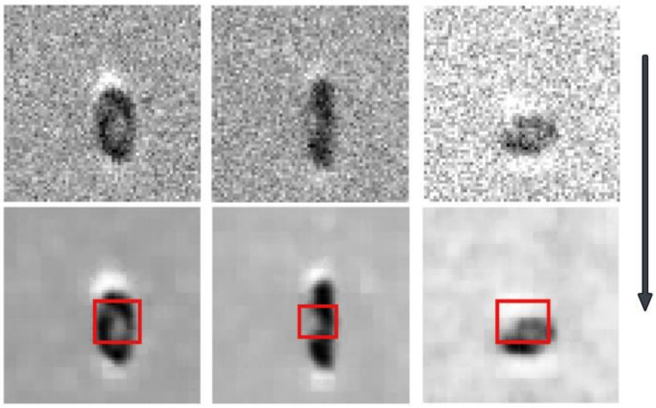


Fig -1 Usage of our CNN model. Top row represents the noisy images, while bottom row depicts the corresponding denoised outputs.

Additionally, these microscopic organisms form the base of the marine food web. By converting inorganic nutrients into organic matter, they provide the primary food source for a wide range of marine organisms, from tiny zooplankton to larger filter-feeding whales [3]. Their abundance, distribution, and health directly impact the availability of food for subsequent trophic levels and can influence the abundance and health of fish stocks that many global economies rely on.

Given their diversity, phytoplankton can be categorized into various groups, each with its unique set of characteristics. Some of the prominent groups include diatoms, known for their siliceous cell walls; dinoflagellates, many of which can produce toxins leading to harmful algal blooms; and cyanobacteria, some species of which are responsible for nitrogen fixation in marine environments [4].

Understanding the ecology, physiology, and distribution of these groups is essential for predicting how changes in the marine environment, such as ocean warming or acidification, might impact marine ecosystems at large. This prediction underscores the necessity for robust monitoring mechanisms. Consequently, remote sensing techniques like satellite measurements of surface chlorophyll-a concentration have provided unparalleled insights into phytoplankton variability at global scales [5]. Such observations have shed light on both the spatial and temporal changes in phytoplankton biomass, from their predictable seasonal cycles to fluctuations caused by oceanic phenomena like upwelling.

However, interpreting these images is often met with challenges due to noise [6]. While electronic noise from imaging equipment is a recognized issue, it's essential to correctly understand and represent potential biological interferences [7], [8]. To enhance the accuracy of species classification and address these challenges, our research proposes the use of CNNs, the details of which will be elaborated upon in the subsequent sections.

2. RELATED WORK

To the best of our knowledge, there has not been any study specifically aiming to denoise microscopic images of phytoplanktons as of yet. However, there have been studies focusing on the identification, segmentation, and classification of these organisms using both traditional algorithms and neural networks.

One noteworthy study [9] looks into the development of a computer-based image processing technique for automated detection and classification of a handful of algae genera. Their approach involved image preprocessing, feature extraction, and classification through artificial neural networks (ANNs). While successful in classifying algae genera from various divisions, they encountered significant noise challenges. Their solution involved traditional image processing algorithms, such as median filtering, for noise reduction; their primary target being the recognition of freshwater algae. This highlights a potential research gap in the application of deep learning techniques for denoising such images.

Another group of researchers introduced an automatic identification method for harmful algae using multiple convolutional neural networks and transfer learning [9]. A key aspect of their methodology was the employment of image augmentation techniques, specifically noise addition, to counteract imbalanced datasets. While this augmentation technique likely improves model robustness by introducing more variability, it simultaneously highlights the importance of efficient denoising techniques. Intentional addition of noise to datasets for training can potentially result in real-world images being confounded with augmented noise during analysis. This raises the need for advanced denoising techniques, ensuring the model isn't misinterpreting or misclassifying due to the artifacts introduced during augmentation.

Previous studies have also explored the use of CNNs for denoising in CT imaging, highlighting both their potential and the associated challenges [11]. A primary concern raised was the ability of CNNs to generalize across varied data. If not trained with diverse and representative data, CNN models can become overly specific to their training set and fail to generalize across different clinical conditions. Although the field of medical CT scanning differs from that of phytoplankton microscopy, the underlying challenges of image clarity and interpretability are shared. In our research, employing CNNs to denoise microscopic images of phytoplankton, we took into account the challenges highlighted by Huber et al. As a solution, we trained our model on an extensive dataset of 10,524 images. By carefully designing our model architecture and employing regularization techniques, we aimed to promote generalization and reduce overfitting, thereby enhancing the model's applicability in real-world scenarios.

Further work has been conducted in the field of image denoising for various applications. For instance, a study done in 2019 introduced a CNN-based approach for denoising stimulated Raman scattering (SRS) microscopy images, which are commonly used in biomedical and chemical research [12]. They highlighted the use of CNNs in denoising nonlinear optical images, specifically SRS images. Additionally, other deep learning methods have also been successfully applied to denoise diverse image types, including retinal microvasculature images obtained through optical coherence tomography angiography [13], and astronomical images [14].

While these methodologies provide valuable insights, there is limited research specifically targeting the denoising of phytoplankton images, or other microscopic marine algae for that matter. Our work aims to fill this gap and further the field's understanding of image denoising techniques for marine microscopic organisms.

3. METHODOLOGY

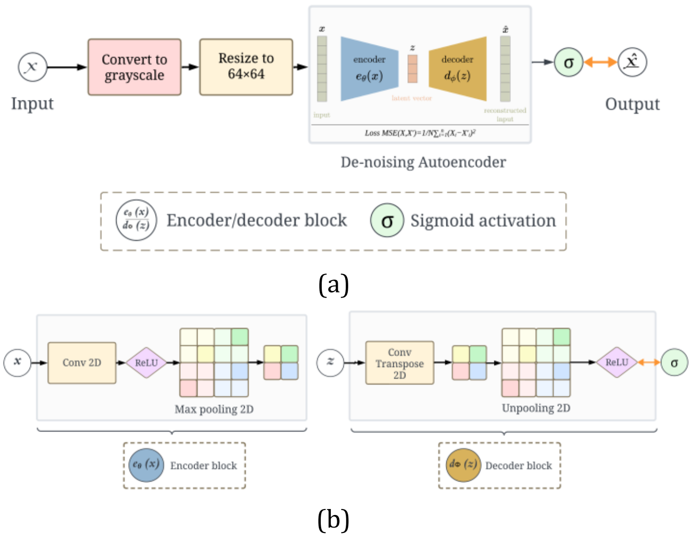


Fig -2: (a) Architecture of our CNN model and the step-by-step pipeline of the denoising process. (b) The encoder-decoder blocks constituting the autoencoder structure.

We structured our methodology into distinct stages: 1) data gathering, 2) image preprocessing to ensure compatibility with the neural network, 3) introducing noise types (Gaussian, salt and pepper, and speckle) to create training data, and 4) training our model using these noisy images and evaluating its performance across standard metrics.

3.1. DATASET GATHERING

We gathered data from the WHOI-Plankton dataset, which is popular for its comprehensive collection of phytoplankton species, consisting of 103 distinct classes. Given the limited prior research specifically focused on denoising such data, we identified this dataset as particularly suitable for our objectives. From this dataset, we extracted a subset of 10,524 images, striving to represent all the classes uniformly. This raises the need for standard image preprocessing practices, ensuring the model isn't misinterpreting or misclassifying due to any incompatibilities.

First, we resized all the data to a standard size of 64x64 pixels to ensure high scalability and efficiency while also balancing the trade-off with accuracy. Furthermore, we normalized all the images in our dataset to a range of pixel values between 0 and 1. Normalization serves several purposes. It accentuates the contrast and brightness of images, bringing forth details and features potentially concealed in the original image [15]. It ensures image comparability; consistent pixel values allow for meaningful contrasts between different images or within specific regions of the same image. Moreover, adjusting to a standardized pixel distribution minimizes the influence of outliers and amplifies the image's overall quality [16].

3.2 INTRODUCING NOISE

Having established the data gathering and normalization process, our next focus was to introduce realistic noise to the dataset to simulate the challenges typically encountered in microscopy. The noise introduction was facilitated by a composite function, capable of inducing three distinct types of noise: Gaussian, salt and pepper, and gamma speckle.

1. Gaussian Noise: We utilized a normal distribution with a mean of zero and a standard deviation of 0.1 to produce Gaussian noise, which models electronic interference during the acquisition process [17].

2. Salt and Pepper Noise: This type of noise introduced extreme values (either completely white or completely black pixels) at random locations [18]. Our function introduced this noise such that approximately 0.5% of the image pixels would be affected, modelling artifacts such as dead pixels or impulsive noise.

3. Gamma Speckle Noise: Gamma noise is applied multiplicatively, modulating the original pixel values. It can emulate inconsistencies introduced during the image acquisition process, especially when using certain types of sensors.

Once the noise was added, the image data was split into training, validation, and test sets, using an approximately 70-15-15% distribution. This ensures that our CNN model has a diverse range of data for learning, validating hyperparameters, and evaluating final performance. The following section shows in detail how the model was trained.

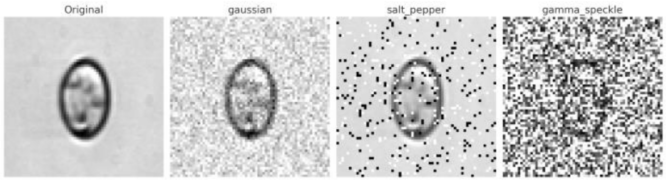


Fig 3. Introduction of different types of noise to the original image. From left to right: the original image, Gaussian noise, salt-and-pepper noise, and speckle noise.

3.3 EXPERIMENTAL DETAILS

This section details the methodology used for denoising images. For our experiments, we employed a Denoising Autoencoder, a model designed to reconstruct input data by learning to represent its noise-free version. The encoder captures the essential features of the noisy image, and the decoder reconstructs the denoised image from these features.

Encoder:

1. Convolutional layer with 64 filters of size 3×3, followed by ReLU activation.
2. Max-pooling with a 2×2 kernel.
3. Another convolutional layer with 128 filters of size 3×3, followed by ReLU activation.
4. Max-pooling with a 2×2 kernel.

Decoder:

1. Transpose convolutional layer with 64 filters of size 2×2, followed by ReLU activation.
2. Another transpose convolutional layer with a single filter of size 2×2, followed by a Sigmoid activation.

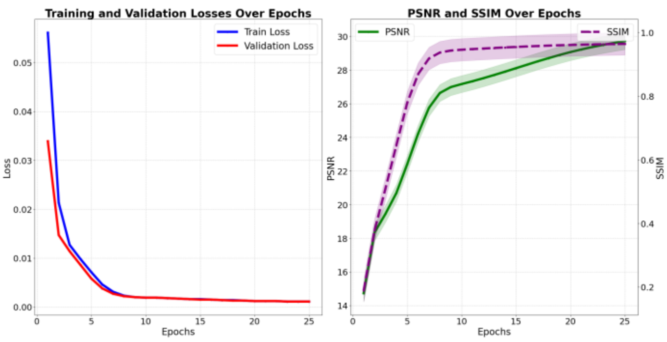
The architecture was selected based on the need to balance model complexity with the computational efficiency, in order for the accurate representation of noise-free images. The model was trained using the Mean Squared Error (MSE) loss function. It quantifies the average squared difference between the predicted and true values. This squaring inherently penalizes larger errors more, thus ensuring that the model is driven to reduce significant deviations. This makes MSE a robust choice for tasks that demand precision, such as ours.

We opted for the Adam optimizer due to its proven computational efficiency, low memory demands, and adeptness at managing large datasets and numerous parameters. Specifically, for denoising tasks, Adam has demonstrated superior performance against several algorithms, especially in scenarios with high-intensity noise. While the initial choice was a learning rate of 0.0001, our preliminary trials indicated that a reduced rate of 0.00001 provided improved convergence. This adjustment aligns with findings suggesting that overly aggressive learning rates in Adam might negatively influence the learned features of the model. For model evaluation, we used the following metrics:

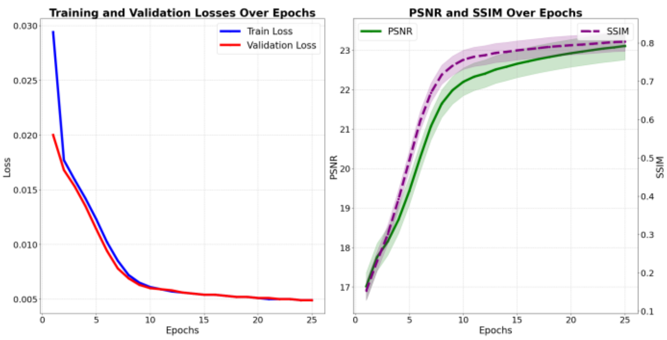
1. PSNR (Peak Signal-to-Noise Ratio): A metric that measures the peak error between the original and the compressed image, indicating the quality of reconstruction.

2. SSIM (Structural Similarity Index): This quantifies image quality degradation as perceived changes in structural information.

3. CNR (Contrast-to-Noise Ratio): Measures the contrast between a signal and background noise in images, offering insights into image clarity.



(a)



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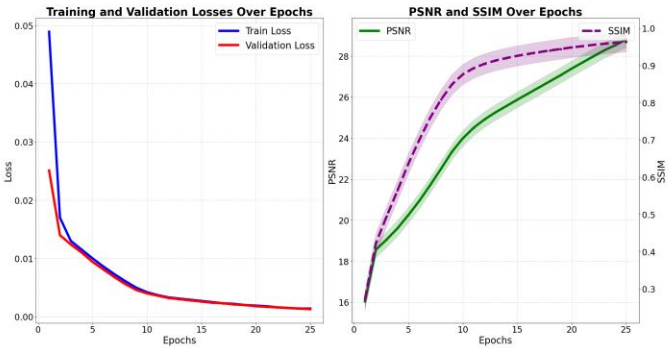

(c)

Fig -4: Training loss, PSNR, and SSIM metrics over each epoch for three denoising conditions: (a) Gaussian, (b) Salt-and-pepper, and (c) Speckle.

Training was conducted for 50 epochs. We implemented early stopping with a patience of 10 epochs, meaning if the validation loss did not show a significant improvement (a delta of 0.001) for 10 epochs, the training will be terminated. Convergence, as evidenced by flattening loss and metrics, was observed after 26 epochs across all noise conditions.

4. RESULTS

Phytoplankton imaging often encounters various types of noise, each presenting unique challenges to image analysis. Three of the most common noise types: Gaussian, Salt and Pepper, and Speckle, are of significant interest in our research. Our model's performance against these noise types provides crucial insights into its accuracy and adaptability. Our CNN was trained over 50 epochs using a dataset of 10,524 noisy phytoplankton images. The dataset was partitioned into training, validation, and test sets with 7,366, 1,579, and 1,579 images, respectively, according to a 70-15-15 split ratio. The variations in training loss, PSNR (Peak Signal-to-Noise Ratio), and SSIM (Structural Similarity Index Measure) as the model progresses through each epoch are presented in **Fig -4.**

Gaussian noise, frequently a result of electronic interference during the image acquisition process, is a prevalent noise type in phytoplankton imaging. The model exhibited a PSNR of 32.08 dB and an SSIM of 0.9788 when handling Gaussian noise. Salt and Pepper noise is characterized by sporadic white and black pixels, potentially arising from abrupt disruptions in the image signal. The model achieved a PSNR of 31.83 dB and an SSIM of 0.9800 for this noise type. However, the model's performance against Speckle noise, originating from graininess or inconsistencies in the imaging medium, was reduced. This reduction in performance signifies the complexity of handling Speckle noise. For this type of noise, the CNN achieved a PSNR of 23.55 dB and an SSIM of 0.8200.

An illustrative figure of our model's predictions when exposed to different noise types is shown in **Fig -5**: Each subfigure consists of three images: starting with the noisy input image, followed by the model's denoised output, and concluding with the ground truth. This side-by-side comparison accentuates the model's efficacy and provides a stark visual representation of the noise reduction achieved. From the above, it's evident that our model exhibits competent performance across all three noise conditions. However, each noise type poses distinct challenges, and while the model handles Gaussian and Salt and Pepper noises with remarkable proficiency, there's a noted decrease in performance metrics for Speckle noise. The performance of our model on different noise conditions, namely Salt and Pepper, Speckle, and Gaussian, was assessed. The metrics used for evaluation were Test Loss, PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and CNR (Contrast-to-Noise Ratio).

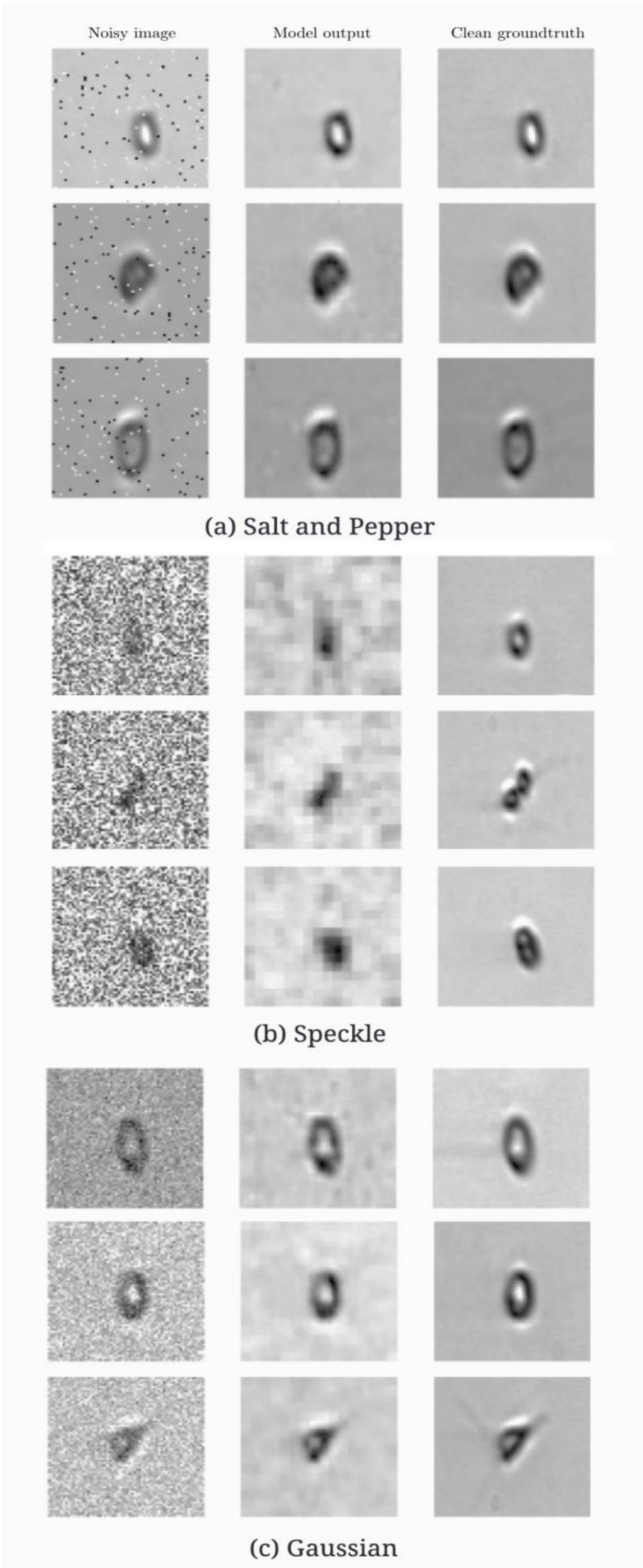

Fig -5. A figure representing our model's predictions when exposed to different noise types.

The performance of our model on different noise conditions, namely Salt and Pepper, Speckle, and Gaussian, was assessed. The metrics used for evaluation were Test Loss, PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and CNR (Contrast-to-Noise Ratio). The results are tabulated below:

Table -1: Comparison of performance

Noise type	PSNR	SSIM	CNR
Gaussian	32.08	0.97	6.22
Salt and Pepper	31.83	0.98	4.19
Speckle	23.55	0.82	2.39

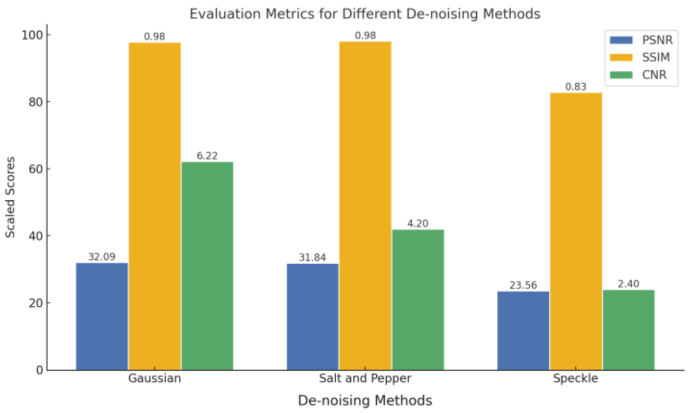

Chart -1: Evaluation of our model's performance on three separate noise conditions.

5. CONCLUSION

One of the primary obstacles faced by researchers in the field of phytoplankton imaging is the degradation of image quality due to inherent noise. This noise, emerging from both the bioluminescence of the phytoplankton and the electronic equipment, can compromise the accuracy of machine learning models aimed at classifying these species. In this paper, we addressed the challenge of image noise by deploying a custom Convolutional Neural Network (CNN) for image denoising. We look forward to further investigations and collaborations that will build upon our work and drive forward the field of phytoplankton research.

REFERENCES

[1] Ward, Ben and Michael J. Follows, 2016. "Marine mixotrophy increases trophic transfer efficiency, mean organism size, and vertical carbon flux", Proceedings of the National Academy of Sciences (11), 113:2958-2963. https://doi.org/10.1073/pnas.1517118113

[2] Barton, Andrew D., Stephanie Dutkiewicz, Glenn R. Flierl, Jason G. Bragg, and Michael J. Follows, 2010. "Response to comment on "patterns of diversity in marine phytoplankton"", Science (5991), 329:512-512. https://doi.org/10.1126/science.1190048

[3] Saifullah, Asm, Abu Hena Mustafa, Mohd Hanafi Idris, Amy Rajaee, and Md. Khurshid Bhuiyan, 2015. "Phytoplankton in tropical mangrove estuaries: role and interdependency", Forest Science and Technology (2), 12:104-113. https://doi.org/10.1080/21580103.2015.1077479

[4] See, Jason, Lisa Campbell, Tammi L. Richardson, James L. Pinckney, Ruijie Shen, and Norman L. Guinasso, 2005. "Combining new technologies for determination of phytoplankton community structure in the northern Gulf of Mexico 1", Journal of Phycology (2), 41:305-310. https://doi.org/10.1111/j.1529-8817.2005.04132.x

[5] Keerthi, M. G., Channing J. Prend, Olivier Aumont, and Marina Lévy, 2022. "Annual variations in phytoplankton biomass driven by small-scale physical processes", Nature Geoscience (12), 15:1027-1033. https://doi.org/10.1038/s41561-022-01057-3

[6] Hong, Seong-Jae, Won-Kyung Baek, and Hyung-Sup Jung, 2020. "Ship detection from x-band SAR images using m2det deep learning model", Applied Sciences (21), 10:7751. https://doi.org/10.3390/app10217751

[7] Polichetti, Maxime, Valentin Baron, Jerome Mars, and Barbara Nicolas, 2021. "Multiplane deconvolution in underwater acoustics: simultaneous estimations of source level and position", JASA Express Letters (7), 1. https://doi.org/10.1121/10.0005513

[8] Kawahito, Shoji and Min-Woong Seo, 2016. "Noise reduction effect of multiple-sampling-based signal-readout circuits for ultra-low noise CMOS image sensors", Sensors (11), 16:1867. https://doi.org/10.3390/s16111867

[9] Mosleh, Mogeeb A. A., Hayat Manssor, Sorayya Malek, Pozi Milow, and Aishah Salleh, 2012. "A preliminary study on automated freshwater algae recognition and classification system", BMC Bioinformatics(S17), 13. https://doi.org/10.1186/1471-2105-13-s17-s25

[10] Yang, Mengyu, Wensi Wang, Qiang Gao, Chen Zhao, Caole Li, Xiangfei Yang, Jiaxi Li et al., 2022. "Automatic identification of harmful algae based on multiple convolutional neural networks and transfer learning", Environmental Science and Pollution Research (6), 30:15311-15324. https://doi.org/10.1007/s11356-022-23280-6

[11] Huber, Nathan R., A. Missert, Lifeng Yu, Shuai Leng, and Cynthia H. McCollough, 2021. "Evaluating a convolutional neural network noise reduction method when applied to CT images reconstructed differently than training data", Journal of Computer Assisted Tomography (4), 45:544-551. https://doi.org/10.1097/rct.0000000000001150

[12] Manifold, Bryce, Elena C. Thomas, Andrew T. Francis, Andrew H. Hill, and Dan Fu, 2019. "Denoising of stimulated raman scattering microscopy images via deep learning", Biomedical Optics Express (8), 10:3860. https://doi.org/10.1364/boe.10.003860

[13] Kadomoto, Shin, Akihito Uji, Yuki Muraoka, Tadamichi Akagi, and Akitaka Tsujikawa, 2020. "Enhanced visualization of retinal microvasculature in optical coherence tomography angiography imaging via deep learning", Journal of Clinical Medicine (5), 9:1322. https://doi.org/10.3390/jcm9051322

[14] Liu, Tie, Yuhui Quan, Yingna Su, Y. Guo, S. Liu, Haisheng Ji, Qing Hao et al., 2023. "Denoising astronomical images with an unsupervised deep learning-based method. https://doi.org/10.21203/rs.3.rs-2475032/v1

[15] Ntziachristos, Vasilis, Gordon M. Turner, Joshua Dunham, Stephen D. Windsor, Antoine Soubret, Jorge Ripoll, and Helen A. Shih, 2005. "Planar fluorescence imaging using normalized data", Journal of Biomedical Optics (6), 10:064007. https://doi.org/10.1117/1.2136148

[16] Dobeck, G. J. (2005). Image normalization using the serpentine forward-backward filter: application to high-resolution sonar imagery and its impact on mine detection and classification. SPIE Proceedings. https://doi.org/10.1117/12.602878

[17] Aslan, Muhammet Fatih, Akif Durdu, and Kadir Sabanci, 2019. "A comparison study for image denoising", European Journal of Technic. https://doi.org/10.36222/ejt.623068

[18] Ali, Suhad A., C. Elaf A. Abbood, and Shaymaa Abdu lKadhm, 2016. "Salt and pepper noise removal using resizable window and gaussian estimation function", International Journal of Electrical and Computer Engineering (IJECE) (5), 6:2219. https://doi.org/10.11591/ijece.v6i5.pp2219-2224

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