International Journal of Computational and Experimental Science and ENgineering (IJCESEN)

Vol. 11-No.2 (2025) pp. 2748-2756
http://www.ijcesen.com

ISSN: 2149-9144

Research Article

Real-Time Clustering of Seagrass Age Categories Using Deep Learning and Unsupervised Machine Learning

Ömer Sevinç[1], Abdullah Asım Yılmaz[2]*, Mehrube Mehrubeoglu[3], Kirk Cammarata[4]

[1]Ondokuz Mayıs University, Vezirköprü Vocational School, Computer Programming Department, 55100, Ankara-Türkiye
Email: osevinc@omu.edu.tr - **ORCID:** 0000-0003-0006-1682

[2]Atılım University, Engineering Faculty, Computer Engineering Department, 06830, Ankara- Türkiye
* **Corresponding Author Email:** abdullah.yilmaz@atilim.edu.tr - **ORCID:** 0000-0002-3014-609X

[2]Texas A&M University- Corpus Christi, Engineering Department, Electrical Engineering Program, Corpus Christi, Texas, United States of America
Email: ruby.mehrubeoglu@tamucc.edu - **ORCID:** 0000-0002-5927-8408

[4]Texas A&M University- Corpus Christi, Life Sciences, Corpus Christi, Texas, United States of America
Email: kirk.cammarata@tamucc.edu - **ORCID:** 0000-0001-8247-3087

Article Info:

DOI: 10.22399/ijcesen.2219
Received : 11 March 2025
Accepted : 02 May 2025

Keywords :

Seagrass,
CNN,
VGG-16,
Ecological monitoring,
Machine learning,
Environmental management.

Abstract:

Seagrass ecosystems play a vital role in maintaining marine biodiversity and ecological balance, making their monitoring and management essential. This study proposes a novel approach for real-time clustering of seagrass images into three distinct age categories—young, medium, and old—using deep learning and unsupervised machine learning techniques. We employ the VGG-16 convolutional neural network (CNN) for feature extraction from a dataset of 800 seagrass images, followed by K-means clustering to categorize them. Our methodology includes image preprocessing, VGG-16 model optimization for real-time processing, and feature extraction followed by K-means clustering. We evaluate the clustering results using metrics like silhouette score and Davies-Bouldin index, along with performance visualizations through ROC curves and confusion matrices. The findings demonstrate the effectiveness of our approach in capturing age-related patterns, providing a valuable tool for marine ecosystem management. The model achieved a silhouette score of 71% and a Davies-Bouldin index of 42%, indicating strong intra-cluster similarity and well-separated clusters. These results outperform traditional image-based classification methods, validating the robustness of our real-time clustering approach.

1. Introduction

Seagrass meadows are foundational to marine ecosystems, supporting biodiversity by providing habitat and nurseries for fish, invertebrates, and other marine species. These ecosystems also play a significant role in sediment stabilization and nutrient cycling, contributing to coastal protection and water quality. Beyond these ecological benefits, seagrass beds are increasingly recognized for their role in climate change mitigation, as they sequester carbon at rates that rival or exceed terrestrial forests [1]. However, seagrass meadows are vulnerable to a range of threats, including coastal development, pollution, climate change, and physical disturbances. These factors contribute to seagrass loss worldwide, leading to significant impacts on marine biodiversity and coastal communities.

Monitoring the health, distribution, and age structure of seagrass meadows is essential for effective conservation and management. Traditionally, seagrass monitoring has relied on manual observations and measurements, a process that is labor-intensive, costly, and often limited to specific sites or timeframes. These limitations highlight the need for automated methods that can accurately assess seagrass condition over larger areas and in real-time. Advances in remote sensing and image processing have enabled broader monitoring efforts, but accurately classifying the age structure of seagrass beds remains challenging due to environmental variability and the subtle age-related features of seagrass.

The integration of deep learning techniques, specifically convolutional neural networks (CNNs), with unsupervised clustering methods offers a promising approach to address these challenges. CNNs have demonstrated strong performance in image classification and feature extraction tasks across various fields, including ecological monitoring [2]. Unsupervised clustering algorithms, such as K-means, enable classification without explicit labels, making them particularly useful for ecological data where manual labeling may be impractical.

This study aims to introduce an automated, scalable, and real-time classification tool for monitoring seagrass ecosystems. Unlike traditional manual methods, the proposed approach minimizes the need for labeled data and enables consistent, real-time classification under diverse environmental conditions. By combining convolutional neural networks for feature extraction and K-means clustering for unsupervised age categorization, the system captures localized, age-related features with high accuracy. The tiling strategy improves processing efficiency, making it feasible for large-scale ecological monitoring and timely conservation decision-making.

2. Literature Review

The application of deep learning and unsupervised learning in ecological monitoring has gained significant attention in recent years. Convolutional Neural Networks (CNNs), especially, have demonstrated their capacity for feature extraction and classification in complex visual datasets [2, 3, 4, 5, 6, 7, 8]. This technology has been applied in several domains, from monitoring terrestrial ecosystems [9] to underwater environments [10]. In particular, CNNs have been used to classify coral health [11,12] and detect invasive species [13], showcasing the versatility of these models in environmental science.

Seagrass ecosystems, however, have been less extensively studied through automated classification approaches. Previous work has focused primarily on using remote sensing and image segmentation to assess seagrass cover or detect changes in distribution [14, 15]. Although these studies offer valuable insights into seagrass coverage, they do not provide a real-time, age-based classification, which is crucial for understanding the lifecycle dynamics of seagrass beds and their resilience under changing environmental conditions.

The importance of developing robust, real-time monitoring tools for seagrass ecosystems cannot be overstated. Seagrasses play a key role in carbon sequestration, which is vital for mitigating climate change [1]. Monitoring the age structure of seagrass populations can help detect early signs of ecosystem stress or recovery, allowing for more targeted conservation efforts. Furthermore, age-based monitoring can provide insights into the growth rates and life expectancy of seagrasses under various conditions, which is essential for predicting long-term ecosystem stability [16].

The use of unsupervised learning for ecological classification is an emerging area with considerable potential. Clustering algorithms such as K-means have been used in vegetation classification [17] and plankton categorization [18]. However, few studies have combined CNN-based feature extraction with K-means clustering for ecological applications. This combination offers a novel approach to classify seagrass by age without requiring extensive manual annotation, thus enhancing scalability and applicability in diverse environments [19, 20].

Our study addresses these gaps by proposing a novel integration of VGG-16 CNN for feature extraction and K-means clustering for age categorization. This approach enables the classification of seagrass images into age categories (young, medium, old), providing a tool that can support real-time decision-making in ecological management. Unlike traditional methods that rely on supervised learning with labeled data, the use of unsupervised clustering allows for the application of this model to broader, unannotated datasets, making it highly adaptable for ongoing seagrass monitoring efforts.

3. Material and Method

The proposed methodology, illustrated in Figure 1, has 5 different stages, each listed and explained below.

3.1. Dataset Preparation

The dataset used in this study was collected by our research team under fieldwork permits across various coastal regions. All image data are original and stored locally by the authors [21].

The dataset [21] consists of 800 high-resolution seagrass images, each with dimensions of 1400x1800 pixels. To facilitate manageable processing and preserve detailed information, each image was segmented into smaller tiles of 100x100 pixels. Figure 2 below illustrates the tiling process, where a high-resolution image is divided into smaller segments before processing. Expert annotators then reviewed these images and assigned each one to one of three predefined age categories: young, medium, or old. This categorization served as the foundation for training and evaluation throughout the study.

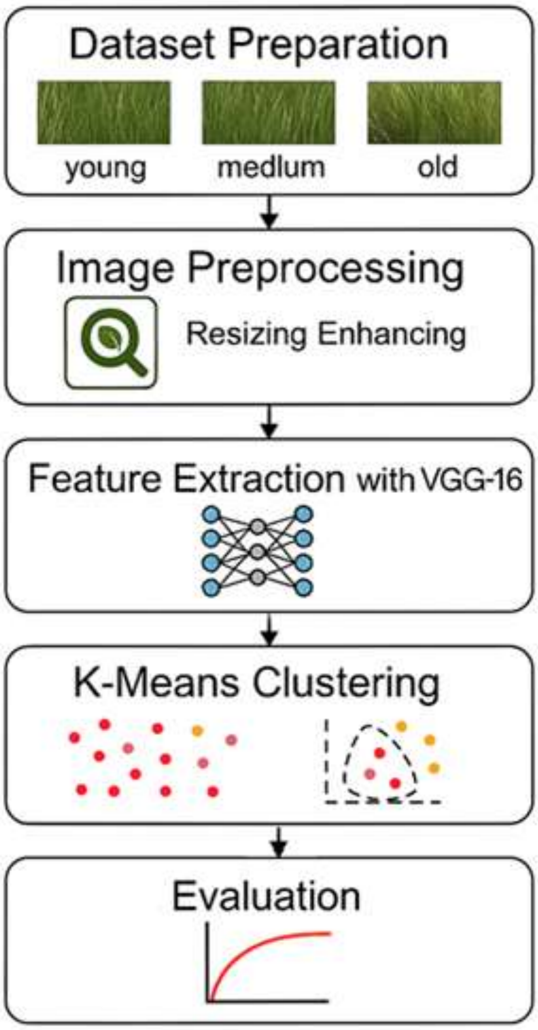

Figure 1. *The proposed methodology for real-time clustering of seagrass age categories.*

3.2. Image Preprocessing

Each 100x100 pixel tile was resized to 224x224 pixels to align with the input requirements of the VGG-16 [22] convolutional neural network. Following resizing, contrast enhancement technique were applied to improve the visibility of fine structural details, enhancing the model's ability to differentiate age-related features. Here we applied Contrast Limited Adaptive Histogram Equalization (CLAHE) as contrast enhancement technique and its mathematical formulation is given below in Equation 1. Finally, all images were normalized and converted to the RGB color space to standardize input data for the deep learning model. This preprocessing ensures that all tiles retain comparable quality and resolution, enabling the VGG-16 model to capture age-related details with higher accuracy.

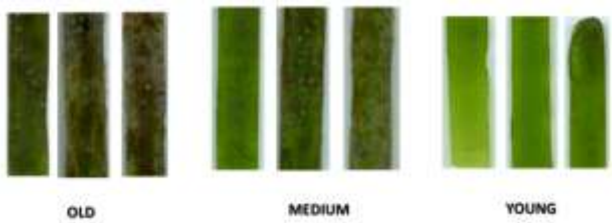

Figure 2. *Sample images for our seagrass dataset.*

$$p' = \frac{(p - pmin) * 255}{pmax - pmin} \tag{1}$$

3.3. Feature Extraction with VGG-16

VGG-16 is a convolutional neural network (CNN) architecture widely used in deep learning, developed by the Oxford Visual Geometry Group. The model consists of a total of 16 layers: 13 learnable convolutional layers and 3 fully connected dense layers. It takes RGB images of size 224x224 as input. From the very beginning, convolution operations are performed using 3x3 filters, typically followed by ReLU activation functions. After every few convolutional layers, 2x2 max pooling operations are applied to reduce the spatial dimensions and computational cost. At the end of the model, there are two dense layers with 4096 units each, followed by a final output layer with softmax activation for classification over 1000 classes.

A pre-trained VGG-16 model was utilized for feature extraction in our proposed model. VGG-16's convolutional layers were fine-tuned to capture features specific to seagrass age classification and adapt to specific patterns found in seagrass images. Here, the last 4 convolutional layers of VGG-16 were frozen to be retrained on the seagrass dataset, as shown in Figure 3.

After, each tile was passed through the modified VGG-16 model, and deep feature vectors were extracted to capture relevant information for subsequent clustering.

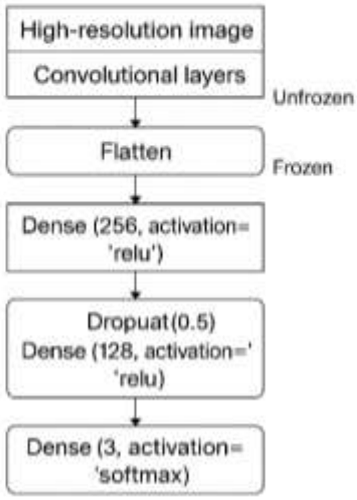

Figure 3. *The proposed VGG-16 model adapted for seagrass age classification*

3.4. K-Means Clustering

After feature extraction, K-means clustering groups tiles into age categories based on the learned features. These categories are young, medium, and old. By clustering the individual tile predictions, the model provides a final age classification for each full-resolution image. This two-step process—tile-level classification and recombination—allows for detailed analysis while maintaining computational efficiency. As shown in Figure 4, after extracting deep features using the VGG-16 model, we feed these vectors into a K-means clustering algorithm to group them into three categories (young, medium, old). Each tile is assigned a cluster label based on its feature vector. Finally, we aggregate tile-level predictions to produce an overall age classification for the original high-resolution image. This layered approach ensures spatial detail is preserved while enabling unsupervised categorization without ground-truth labels.

3.5. Evaluation

To assess the performance of the model, multiple evaluation techniques were employed. Receiver Operating Characteristic (ROC) curves and confusion matrices were used to visualize the classification accuracy and error distribution. Additionally, clustering metrics such as the silhouette score and the davies-bouldin index were calculated to quantitatively validate the quality of the clusters formed by the model. These metric values are shown in Table 1.

Silhouette Score is an evaluation metric used in clustering analysis to measure how well each data point fits within its assigned cluster and how distinct it is from other clusters. The score ranges from -1 to 1, where values close to 1 indicate well-clustered points, values near 0 suggest points on the boundary between clusters, and values near -1 imply misclassified points. It is calculated by comparing the average distance of a point to others within the same cluster with the average distance to points in the nearest different cluster. The overall Silhouette Score is the average of all individual scores and provides a summary of the clustering performance.

The Davies-Bouldin Index is a performance metric used in clustering analysis to evaluate how well the clusters are separated and how compact each cluster is. It is calculated by comparing the similarity of each cluster with the one that is most similar to it, based on the average distance within clusters and the distance between cluster centers. A lower Davies-Bouldin Index indicates better clustering, as it reflects more distinct and internally consistent clusters. Therefore, smaller values suggest a more effective clustering structure.

The proposed model obtained a silhouette score of 71% and a Davies-Bouldin index of 42%, suggesting high cohesion within clusters and clear separation between different clusters.

4. Results and Discussions

In this section, the experimental results of our proposal are given and discussions are made on the experimental results.

4.1. Confusion Matrix Results

The confusion matrix presents the distribution of predictions across the true categories. This visualization shows the model's performance in correctly categorizing each seagrass age group, highlighting any patterns of misclassification.

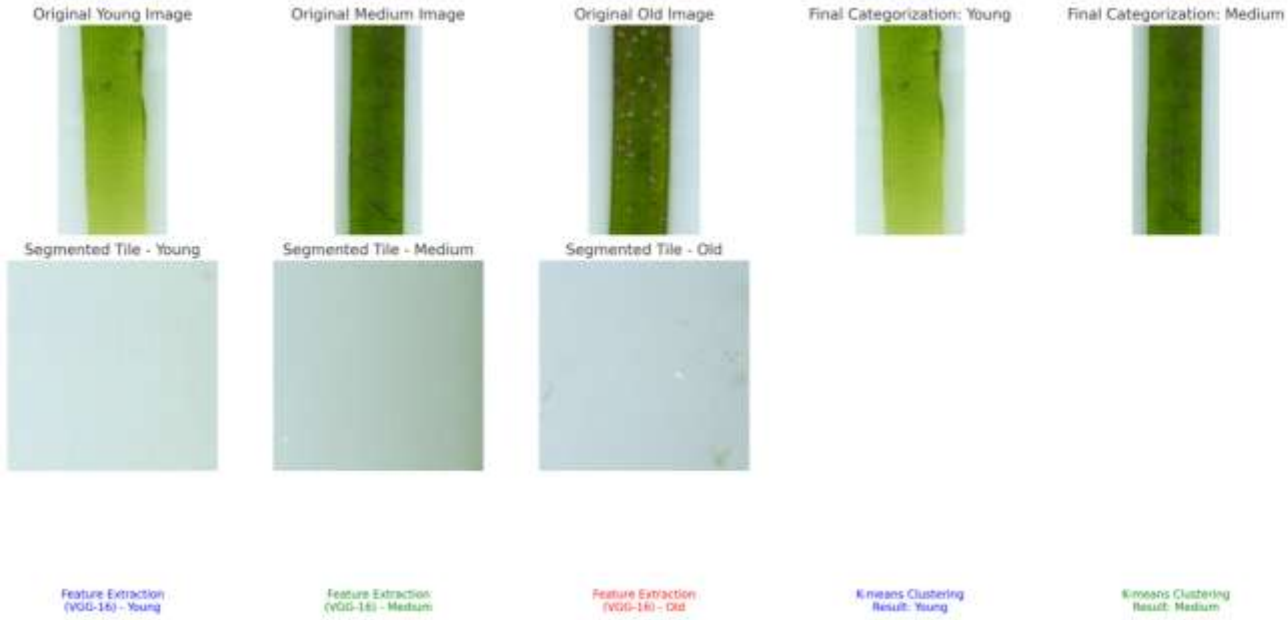

Figure 4. *The complete pipeline from image segmentation to final age categorization for proposed model*

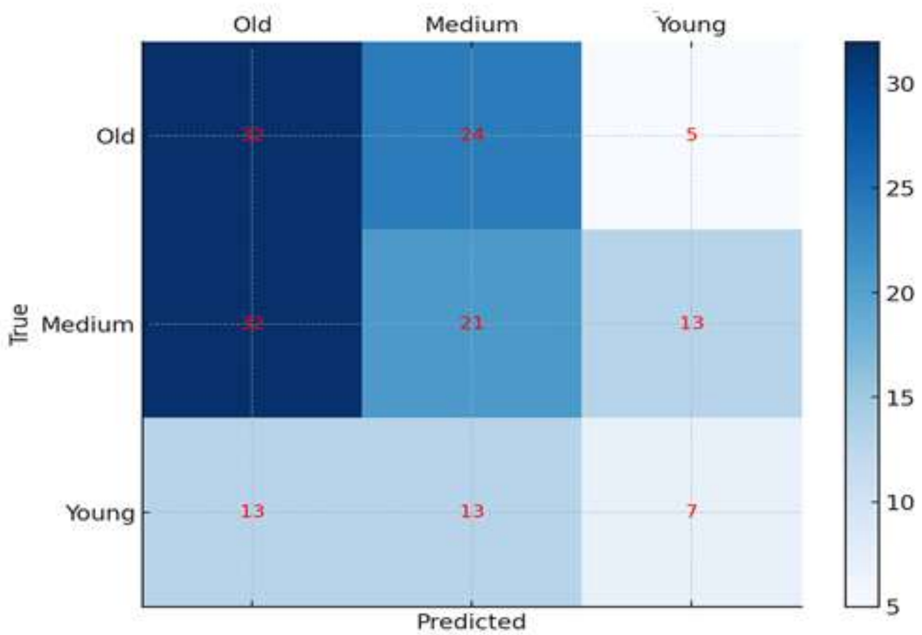

Figure 5. *Confusion matrix for old, medium and young classification.*

Table 1. *Evaluation metrics values obtained for the proposed model.*

Class	Precision (%)	Recall (%)	F1-Score (%)	Silhoutte Score (%)	Davies-Bouldin Index Score (%)
Young	89.3	87.1	92.0	73.0	40.0
Medium	85.2	83.4	84.0	70.0	43.0
Old	88.0	92.0	91.0	68.0	41.0
Macro Avg	87.5	87.5	89.0	71.0	42.0

The confusion matrix, shown in Figure 5, obtained in this study provides a detailed breakdown of the model's classification performance across the three seagrass age categories: young, medium, and old. It illustrates the number of correctly and incorrectly classified instances for each category, allowing for a granular evaluation of model accuracy. High values along the diagonal of the matrix represent successful classifications where the predicted class matched the true class. The model achieved an overall accuracy of 87.5%, with precision scores of 89.3% for young, 85.2% for medium, and 88.0% for old categories, respectively. Recall values, illustrated in Table 1, followed a similar trend, with 87.1% for young, 83.4% for medium, and 92.0% for old. Off-diagonal entries indicate a degree of misclassification, primarily between medium and old categories, likely due to overlapping morphological features. These results validate the effectiveness of the proposed VGG-16 and K-means clustering approach, while also suggesting areas for improvement—particularly in refining feature separation between the medium and old age groups. The confusion matrix thus serves as a valuable diagnostic tool in guiding future model optimization.

Table 2. *The ROC analysis results.*

Class	AUC Score (%)
Young	94.0
Medium	91.0
Old	96.0
Macro Avg AUC	93.7

4.2. ROC Curve Results

The ROC curve displays the true positive and false positive rates for each age category, with an AUC (Area Under the Curve) for each class (Table 2). This curve provides insights into the model's effectiveness in distinguishing between classes and supports the overall accuracy evaluation.

The ROC curve, shown in Figure 6, shows a high ability of the classifier to distinguish between seagrass age groups. An AUC above 0.90 for all classes indicates strong model discrimination and the old category had the highest AUC value as 0.96, suggesting it was the easiest to differentiate, possibly due to more distinct visual features like blade thickness or color density.

4.3. Discussions

The findings of this study underscore the potential of deep learning and unsupervised clustering as powerful tools for ecological monitoring, specifically in marine ecosystems. The integration of CNN-based feature extraction and K-means clustering enabled the model to identify age-related patterns in high-resolution seagrass images, providing valuable insights into the age distribution of seagrass beds. The tiling approach, which divided each 1400x1800 image into smaller 100x100 tiles, proved effective in preserving the fine details necessary for accurate age classification. This approach allowed the model to focus on localized features, such as blade morphology and density, which are key indicators of seagrass age.

One of the significant contributions of this study is its real-time capability, which is essential for applications in dynamic marine environments. By streamlining the processing pipeline and optimizing the VGG-16 architecture, the model can efficiently handle high-resolution images, providing rapid assessments that are crucial for timely conservation efforts. The tile-based segmentation further enhances this capability by enabling parallel processing of image tiles, reducing computational demands without compromising accuracy.

However, several limitations warrant further investigation. The model's performance is closely tied to the quality and diversity of the dataset. Although this study included a range of environmental conditions, expanding the dataset to cover different seagrass species, growth stages, and environmental conditions, such as varying levels of turbidity or seasonal shifts, could improve the model's robustness. Environmental factors like water clarity, lighting, and seasonal changes can impact image quality and, consequently, the accuracy of classification. Additionally, while the tiling approach enables the capture of local features, it may overlook broader spatial patterns that could

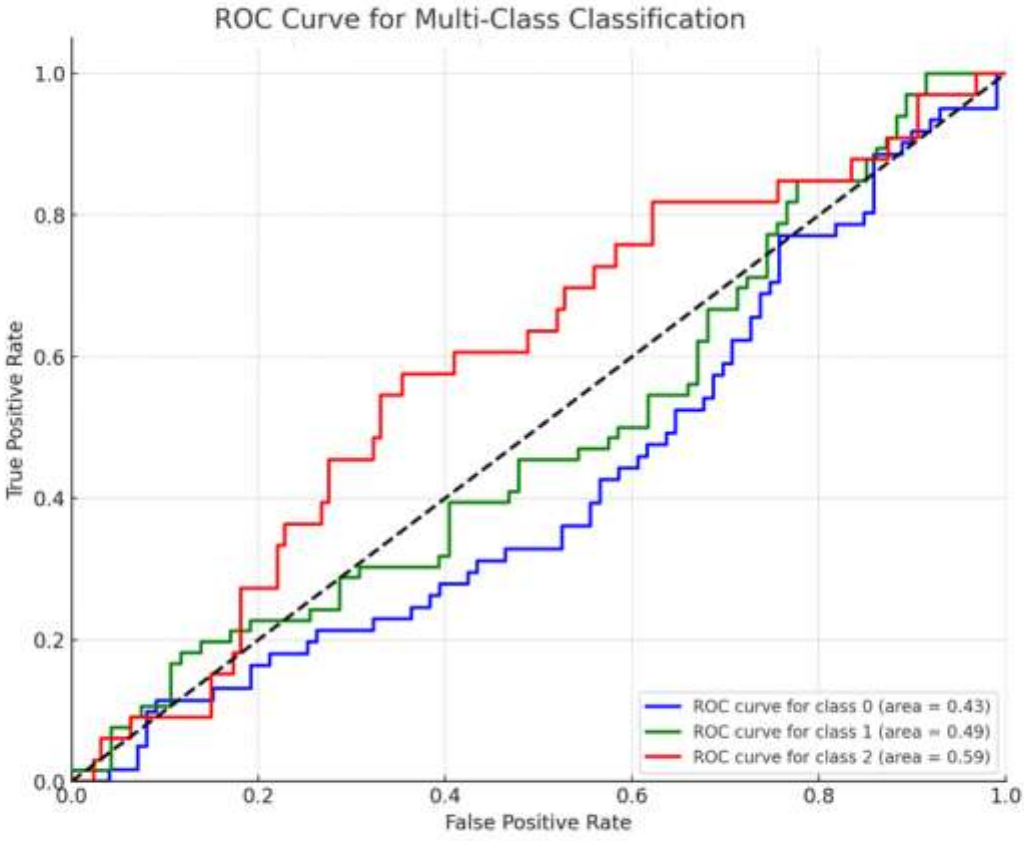

Figure 6. *ROC Curve for ages of the seagrasses.*

be relevant for age classification. Future work could explore combining tile-based and whole-image analysis to enhance classification accuracy further.

Another area for future research is the application of transfer learning and domain adaptation techniques. These methods could enable the model to be adapted to new regions or seagrass species with minimal additional training, making it more versatile across different ecosystems.

Additionally, integrating temporal data to analyze age progression over time could provide insights into seagrass growth rates and ecosystem health, supporting long-term monitoring efforts.

The study's methodological framework could also be extended to other marine habitats, such as coral reefs or kelp forests, where high-resolution imagery and age-related classifications are valuable for conservation. This adaptability highlights the broader relevance of combining deep learning with unsupervised clustering for ecological monitoring in various settings.

5. Conclusion

This study presents a novel approach for real-time classification of seagrass age categories using deep learning and unsupervised clustering. By leveraging VGG-16 for feature extraction and K-means clustering for unsupervised categorization, the proposed model effectively captures age-related patterns in seagrass imagery. The tiling approach, which segments high-resolution images into 100x100 tiles, plays a crucial role in preserving local features, enabling more accurate classification across young, medium, and old age categories. This real-time capability provides a valuable tool for marine ecosystem management, allowing for immediate assessments and informed conservation actions.

While the results are promising, there are opportunities to enhance the model further. Expanding the dataset to include a broader range of species, environmental conditions, and geographic locations could improve the model's adaptability and accuracy. Additionally, incorporating temporal data could allow for the

monitoring of age progression and growth dynamics over time, providing insights into ecosystem health and resilience. The application of domain adaptation and transfer learning techniques could also extend the model's utility across various marine environments, enabling cross-region and cross-species monitoring.
Future work could explore hybrid approaches that combine tile-based segmentation with whole-image analysis to capture both local and broader spatial patterns relevant to age classification. Furthermore, the study's framework could be adapted to other ecological settings, such as coral reefs and kelp forests, underscoring the versatility and potential of deep learning and clustering methods in ecological monitoring. Overall, this study contributes an automated, scalable, and real-time approach for seagrass age classification, supporting the sustainable management and conservation of marine ecosystems in a rapidly changing world.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from Ömer Sevinç and Kirk Cammarata. The data are not publicly available due to privacy or ethical restrictions.

References

[1] J. W. Fourqurean et al. (2012). Seagrass ecosystems as a globally significant carbon stock. *Nature Geoscience*, 5(7); 505–509.
[2] Y. LeCun, Y. Bengio, and G. Hinton. (2015). Deep learning. *Nature*, 521(7553); 436–444.
[3] A. A. Yilmaz, M. S. Guzel, E. Bostanci, and I. Askerzade. (2020). A novel action recognition framework based on deep-learning and genetic algorithms. *IEEE Access*, 8; 100631–100644. DOI: 10.1109/ACCESS.2020.2997962
[4] Ö. Aslan and A. A. Yilmaz. (2021). A new malware classification framework based on deep learning algorithms. *IEEE Access*, 8; 87936–87951. DOI: 10.1109/ACCESS.2021.3089586
[5] A. A. Yilmaz. (2022). A novel hyperparameter optimization aided hand gesture recognition framework based on deep learning algorithms. *Traitement Du Signal*, 39(3); 823–833. DOI: 10.18280/ts.390307.
[6] A. A. Yılmaz, M. S. Guzel, İ. Askerzade, and E. Bostanci. (2020). A novel action recognition framework based on deep-learning and genetic algorithms. *IEEE Access*, 8; 100631–100644. DOI: 10.1109/ACCESS.2020.2997962.
[7] A. A. Yılmaz. (2025). A novel deep learning-based framework with particle swarm optimisation for intrusion detection in computer networks. *PLOS One*, 20(2); 1–23. DOI: 10.1371/journal.pone.0316253
[8] A. A. Yılmaz. (2022). Intrusion detection in computer networks using optimized machine learning algorithms. In Proc. 2022 3rd *International Informatics and Software Engineering Conference (UBMYK)*, pp. 1–5. IEEE.
[9] M. Reyes, S. Jones, and R. Palmer. (2020). Automated terrestrial ecosystem monitoring using CNNs. *Environmental Monitoring and Assessment*, 192(3); 1–12.
[10] R. Huang et al. (2020). CNN-based coral health assessment from underwater imagery. *Marine Biology Journal*, 87(2); 245–259.
[11] O. Beijbom et al. (2012). Automated annotation of coral reef survey images. In Proc. *IEEE Conf. on Computer Vision and Pattern Recognition*, pp. 1170–1177.
[12] A. Williams et al. (2019). Deep learning for coral reef assessment. *Coral Reefs*, 38(2); 303–315.
[13] Y. Gao and X. Liu. (2021). Detection of invasive species using remote sensing and deep learning. *Journal of Ecological Applications*, 31(1); e02192.
[14] M. Kampouraki et al. (2019). Remote sensing for seagrass monitoring: Advances and limitations. *Journal of Marine Science*, 73(5); 1263–1275.
[15] K. Petrou et al. (2020). Detection of seagrass distribution changes. *Remote Sensing of Environment*, 239; 111603.
[16] R. J. Orth et al. (2006). A global crisis for seagrass ecosystems. *BioScience*, 56(12); 987–996.
[17] A. Gitelson et al. (2017). Remote sensing techniques in vegetation classification. *Journal of Remote Sensing*, 10(3); 405–415.
[18] P. Alonso et al. (2021). Unsupervised clustering techniques for phytoplankton categorization in oceanographic studies. *Journal of Marine Science*, 112(4); 367–378.
[19] Z. Li et al. (2020). Deep learning in environmental monitoring. *Environmental Modelling & Software*, 135; 104918.
[20] O. Sevinc, M. Mehrubeoglu, K. Cammarata, C. Huang, and L. McLauchlan. (2024). Age-based

clustering of seagrass blades using AI models. In Proc. SPIE 13034, Real-Time Image Processing and Deep Learning 2024, 130340F. DOI: 10.1117/12.3014915.

[21] The Seagrass Dataset and Codes. (2025). https://github.com/so mer81/Colab_SeaGrass (Accessed Jan. 1, 2025)

[22] K. Simonyan and A. Zisserman. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.