Journal of information and
communication convergence engineering
http://jicce.org

J. Inf. Commun. Converg. Eng. 22(3): 221-230, Sep. 2024 Regular paper

Marine life Image Recognition using Deep Learning

Jiyun Hong[1], Jiwon Lee[1], Somin Lee[1], Eun Ko[1], Gyubin Kim[1], Jungwoon Kang[2*], and Mincheol Kim[2*]

[1]Department of Management Information Systems, Jeju National University, Jeju 63243, Republic of Korea
[2]Faculty of Data Science for Sustainable Growth, Jeju National University, Jeju 63243, Republic of Korea

Abstract

The aim of this study is to investigate the automatic recognition and analysis of Jeju marine-life images using artificial intelligence (AI) technology. The dataset of marine-life images was prepared using tools such as Python, TensorFlow, and Google Colab (Google Colaboratory). We also developed models by training deep learning AI in image recognition to automatically recognize the species found in these images and extract their associated information, such as taxonomy, characteristics, and distribution. This study is innovative in that it uses deep learning technology combined with image-recognition technology for marine biodiversity research. In addition, these results will lead to the development of the marine-life industry in Jeju by supporting marine environment monitoring and marine resource conservation. Furthermore, this study is anticipated to contribute to academic advancement, specifically in the study of marine species diversity.

Index Terms: Jeju, Marine Life Image Analysis, Generative AI Technology, Species Identification, Geographical Distribution

I. INTRODUCTION

Deep learning, a field of artificial intelligence (AI) research, is a subset of machine learning that mimics the behavior of the human brain to perform data clustering and enables predictive analysis through the learning process [1]. This technology has garnered significant attention in the computing domain owing to its robust learning capabilities, and has been widely applied in various fields, such as healthcare, visual recognition, text analysis, and cybersecurity [2]. Additionally, the accessibility of open-source sharing allows for rapid improvement and optimization, thereby accelerating overall development [3].

Recognition technology, a fundamental aspect of AI, generally refers to the technology designed to identify objects through images [4]. The global AI market is expected to reach $36.8 billion by 2025, with the image recognition and tagging segment anticipated to reach approximately $8.1 billion [5].

With the advent of the bioeconomic era, which seeks to solve future human problems, the convergence of technologies that utilize AI is becoming increasingly important in the development of marine biotechnology [6,7].

Against the backdrop of these developments, Jeju Island announced its "Jeju Bio-Industry Development Strategy" in June 2023, expressing its intention to strengthen the competitiveness of the marine bio-industry, through which it seeks to create new added value and strengthen the marine bio-industry [8]. Jeju Island, which occupies approximately 25% of the Republic of Korea's waters, possesses diverse and abundant marine biological resources that offer significant potential for the bio-industry [9]. However, the growth of the bio-industry lags behind that of other regions because of a lack of technology and skilled manpower [10].

This paper presents a plan to develop an automatic recogni-

Received 21 January 2024, **Revised** 26 June 2024, **Accepted** 16 July 2024
***Corresponding Author** Jungwoon Kang (E-mail: ghdduddls@naver.com) Minchoel Kim (E-mail: mck1292@jejunu.ac.kr)
Faculty of Data Science for Sustainable Growth, Jeju National University, Jeju 63243, Republic of Korea

Open Access https://doi.org/10.56977/jicce.2024.22.3.221 print ISSN: 2234-8255 online ISSN: 2234-8883

tion and analysis platform for domestic marine biological resources using Python and TensorFlow. This platform integrates image-recognition technology and AI learning by extracting data on ten species of fish and ten species of seaweed inhabiting Jeju from the National Marine Biological Resources Center [11]. This initiative is expected to promote the revitalization of Jeju's marine bio-industry. Additionally, this research is anticipated to contribute to the management of marine resources and conservation of living organisms and ecosystems by supporting marine environmental monitoring.

II. RELATED WORKS

Among existing studies, examples of image-recognition technology using deep learning include the classification of red-tide organism images using open-source deep learning and the classification of rock images using a TensorFlow-based convolutional neural network (CNN) [12,13].

The classification of red-tide organism images was implemented using the TensorFlow framework and Google's image classification model. In this study, 782 images of 13 species of red-tide organisms found along the coast of the Republic of Korea were selected and classified. The previous CNN model was retrained using TensorFlow to classify the images [12].

Subsequently, rock image classification was conducted using TensorFlow and a CNN inception model. This study followed a similar approach to red-tide organism image classification. In this study, images of 16 rock types from a high school curriculum were generated, a dataset of 734 instances was created, and a fine-tuned learning method was applied. The image files were then converted to the TFRecord format for use as a training dataset in TensorFlow.

Consequently, a rock classification system was developed by adapting a trained model for mobile use using fine-tuning methods and TensorFlow Android [13]. Open-source deep learning and image-recognition technologies are used in various industries. Nevertheless, the analysis of marine life using existing image-recognition technologies exhibits low accuracy owing to uncontrollable factors, such as season, weather, water depth, and complex marine environments [14].

Furthermore, the image classification performance is expected to be further improved by removing image noise and applying additional training datasets that are suitable for the model.

Therefore, in this study, Python was used to perform image preprocessing and a deep learning model was built and trained using TensorFlow. We propose an image-recognition technology that overcomes the limitations of existing research and maintains high accuracy, even in more complex environments.

III. SYSTEM MODEL AND METHOD

A. Research Tools and System Structure

Fig. 1 shows the structure of MobileNetV2 used in this study. MobileNetV2 is a CNN-based model that extracts image features by combining convolutional and pooling layers [15]. TensorFlow, an open-source library developed by Google, is an effective research tool for building artificial neural networks, including CNNs and deep learning models [16]. In our study, we used TensorFlow to build a machine learning system based on artificial neural networks.

The proposed marine-life recognition system consists of dataset construction, model learning, image classification analysis, and output steps, as shown in Fig. 2. In the dataset construction stage, marine-life image data were collected and preprocessed, and the size of the learning dataset was increased through data augmentation. In the model training phase, TensorFlow was used to retrain the pretrained image classification model, monitor cross-entropy and accuracy, and evaluate the model's performance. In the final image classification analysis and output step, the top three classes of prediction results were analyzed, and the results were output using a dictionary in which the corresponding biological information was defined.

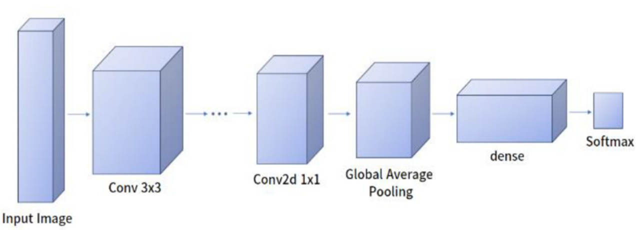


Fig. 1. Convolutional Neural Network (CNN) model structure.

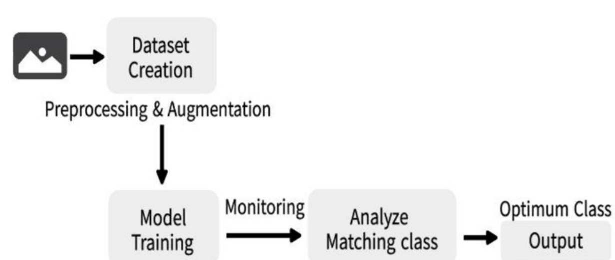


Fig. 2. System structure flowchart.

B. Dataset Creation

1) Data Collection

The scope of the study's dataset was limited to Jeju Island waters, and the top 10 fish and seaweed species were selected based on the occurrence scores of marine life provided by the National Marine Biological Resources Institute. Consequently, images of 20 marine-life species were collected, and 930 datasets were constructed. Table 1 summarizes the 20 marine-life image datasets used in this study.

2) Data Preprocessing

To input the collected data into the image classification model, image files were loaded from the saved locations, and preprocessing was performed on the loaded images. For preprocessing, images of various sizes and resolutions were converted to 224 pixels horizontally and vertically, and adjusted to have RGB color channels.

3) Data Augmentation

In this study, we applied data augmentation techniques to increase the size of the dataset to 3,200. The data augmentation techniques included random rotation up to 40º, image enlargement and reduction up to 0.7-1.3 times, random translation up to 20% each in the vertical direction, shear deformation up to 20º, horizontal inversion, and vertical inversion. The data augmentation method utilizes ImageDataGenerator

Table 1. Jeju marine species dataset

Marine Species	Marine Organisms	Quantity
Fish	Odontamblyopus lacepedii	53
	Dictyosoma burgeri	45
	Pseudopleuronectes yokohamae	48
	Branchiostegus japonicus	45
	Cleisthenes pinetorum	46
	Ostorhinchus semilineatus	45
	Scomber japonicus	45
	Pleuronichthys cornutus	45
	Setipinna tenuifilis	45
	Takifugu niphobles	45
Seaweed	Cladophora wrightiana var. minor	45
	Ulva australis	46
	Padina arborescens	45
	Undaria pinnatifida	46
	Gelidium elegans	47
	Sargassum thunbergii	53
	Codium fragile	50
	Sargassum fusiforme	45
	Ishige okamurae	46
	Colpomenia sinuosa	45
	Total Quantity	930

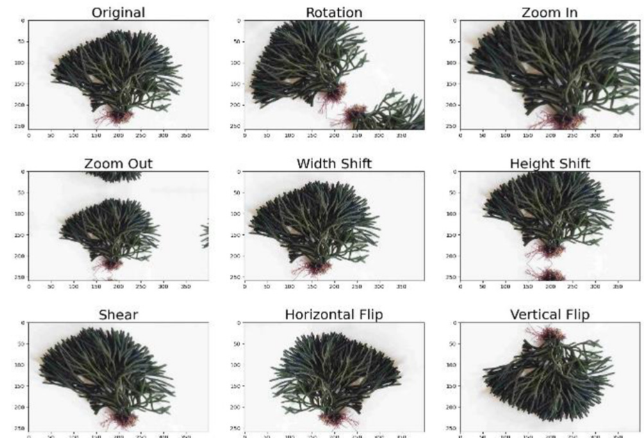


Fig. 3. Marine-life images using data augmentation

to augment images in real time and provide them to the model by location [17]. These augmented data were included in both the training and validation datasets and used to train the model. Fig. 3 shows a visualization of the image using each data augmentation technique applied through ImageDataGenerator.

C. Model Training

In the model-learning stage, the preprocessed image data were applied to the pretrained image classification model to retrain it for marine-life image recognition. We aimed to prevent information loss from image data and increase feature extraction and learning efficiency using a CNN model instead of the existing Deep Neural Network model, which can cause spatial information loss [18].

In this study, we selected a transfer-learning method and used three models: MobileNetV2, InceptionV3, and Xception. Typically, the lower layers of the model learn the universal features of the image, and the upper layers learn the abstract features [19]. Considering these characteristics, we fixed the weights of the lower layers of each model and fine-tuned them by adding a dense layer to the upper layers [20]. Using transfer learning and fine-tuning, the trained model was adjusted to include 20 classification layers. In other words, the existing model loaded through transfer learning was fine-tuned to the marine-life image classification task to minimize loss during learning and increase data efficiency.

To select the optimal model specialized for marine-life recognition, each model was trained ten times, and the accuracies were compared. The model with the best performance was selected for further training.

While monitoring the learning process, we calculated the categorical cross-entropy and accuracy by comparing the predicted and actual values and applied them to the valida-

Table 2. Number of images of learning data, verification data, and test data

Category	Training Data (81%)	Validation Data (9%)	Testing Data (10%)
Original image	754	83	93
Augmented data image	2880	320	93

Table 3. Test data quantity by marine organism

Marine Life	Quantity	Marine Life	Quantity
Ulva australis	5	Undaria pinnatifida	5
Codium fragile	5	Sargassum thunbergii	5
Ishige okamurae	5	Setipinna tenuifilis	5
Odontamblyopus lacepedii	5	Dictyosoma burgeri	4
Branchiostegus japonicus	5	Sargassum fusiforme	4
Gelidium elegans	5	Ostorhinchus semilineatus	4
Pleuronichthys cornutus	5	Scomber japonicus	4
Colpomenia sinuosa	5	Padina arborescens	4
Cleisthenes pinetorum	5	Cladophora wrightiana var. minor	4
Pseudopleuronectes yokohamae	5	Takifugu niphobles	4

tion data. Based on cross-entropy and accuracy, the trained model was evaluated using validation data to estimate the generalization ability of the model and to detect and adjust for overfitting. After completing model tuning, we performed a final evaluation of the model by comparing its accuracy with the training and testing data.

To evaluate the model performance, the marine-life image dataset was structured as shown in Table 2.

Table 2 shows the quantities of training, validation, and test data. The training data for retraining the image classification model comprised 81% of the dataset. The validation data used to estimate the generalization ability of the model consisted of 9% of the dataset. Finally, the test data used to evaluate the performance of the image classification model consisted of 10% images for each marine species through hierarchical sampling. At this time, data augmentation was not applied to the test data; therefore, testing was performed with 93 original images, corresponding to 10% of the total dataset. The number of images for each marine species included in the test data is presented in Table 3.

D. Image Classification Analysis and Output

The final image classification analysis and output step used a dictionary containing mapping information between the images and data based on accuracy. The system is designed to verify the characteristics and distribution information of organisms by combining them with a dictionary when the results are output.

IV. RESULTS

Fig. 4 shows the results of repeatedly training the marine life dataset using MobileNetV2, InceptionV3, and Xception, ten times each.

According to the graph, MobileNetV2 (60%), Xception (54%), and InceptionV3 (34%) exhibited improved performance. Among them, MobileNetV2 showed the highest accuracy of 60%, and the difference in accuracy between the models can be attributed to the structural characteristics of each model [21,22,23].

Fig. 5 shows the structural diagrams of MobileNetV2, InceptionV3, and Xception. First, Fig. 5(a) shows the structure of the MobileNetV2 model. MobileNetV2 uses an inverse residual technique to improve the accuracy by combining layer information. The use of depthwise separable convolutions and techniques to reduce the number of parameters to be optimized has proven to be effective in terms of efficiency by reducing the number of parameters and number of computations required [21]. Fig. 5(b) shows the structure of InceptionV3. InceptionV3 uses an inception block layer. The layer

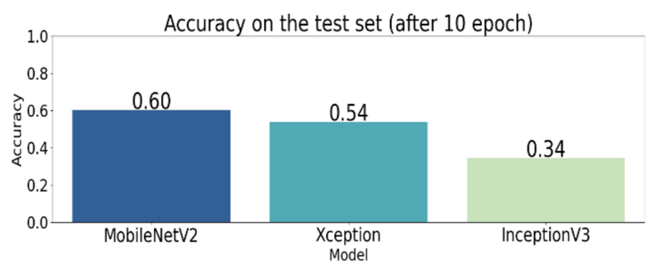


Fig. 4. Model comparison.

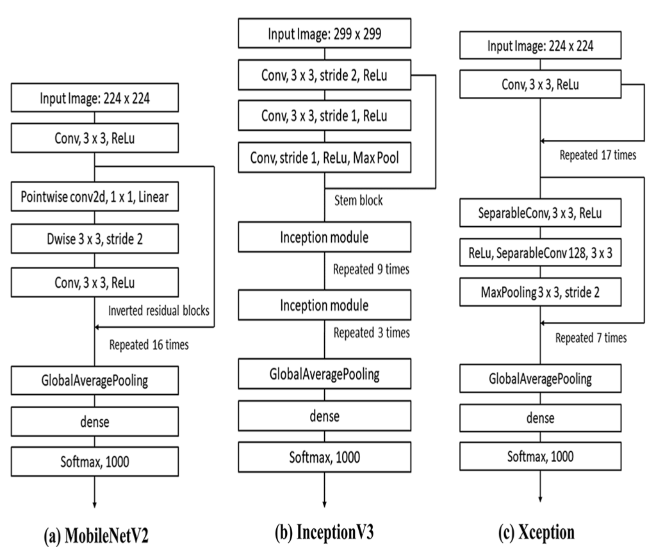


Fig. 5. Structural diagram of each model. (a) MobileNetV2, (b) InceptionV3, and (c) Xception.

consists of parallel convolutional branches with filters of different sizes, and additional processing occurs in the connected branch stages, resulting in more parameters and greater computational complexity than MobileNetV2 [22]. Finally, Fig. 5(c) shows the structure of Xception. Xception uses layers of depthwise separable convolutions and point-wise convolutions, and a data normalization technique that changes based on the input scale. Because an additional depth-specific convolution is used after the depth-separable convolution layer, the model's representation power and computational cost increase compared to those of MobileNetV2 [23].

In other words, MobileNetV2 is designed for efficient computation, and among the three models presented above, it is efficient in many aspects, including parameters, computational efficiency, and number of parameters. However, the Xception and InceptionV3 models use deeper and more complex architectures and additional layers, resulting in many more parameters, longer computation times, and lower efficiency. Therefore, we conducted additional training using MobileNetV2, which exhibited the highest accuracy.

To determine the appropriate learning number for the selected MobileNetV2 model, an iterative learning process was performed 10-200 times, and the accuracy was the highest when performed 100 times. Because there was no significant difference in the number of training repetitions and accuracy, we conducted a study on a model that was trained 100 times.

As a result of monitoring the learning process of the model, the cross-entropy and accuracy graphs are shown in Fig. 6(a).

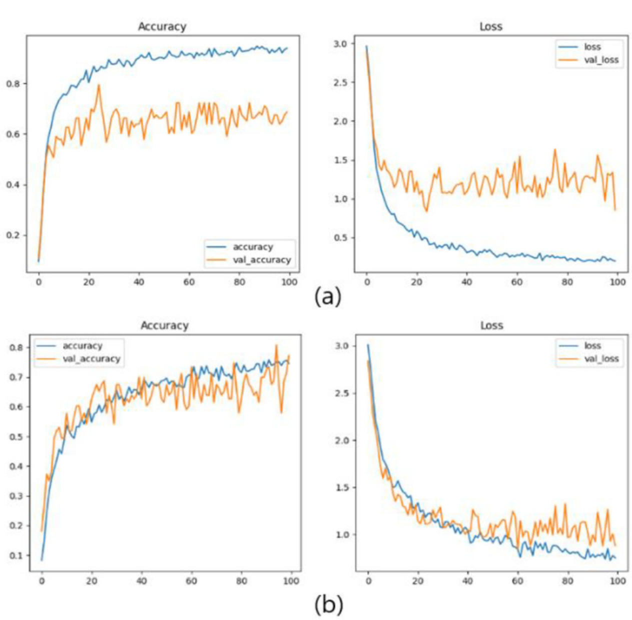


Fig. 6. Comparison of cross-entropy and accuracy graphs based on the presence or absence of dropout. (a) represents the state before the application of dropout, and (b) depicts the state after the incorporation of dropout.

Table 4. Trained image test results

Marine Species	Marine Life	Accuracy(%)
Fish	Odontamblyopus lacepedii	89.0
	Dictyosoma burgeri	94.8
	Pseudopleuronectes yokohamae	89.2
	Branchiostegus japonicus	98.8
	Cleisthenes pinetorum	69.8
	Ostorhinchus semilineatus	88.0
	Scomber japonicus	100.0
	Pleuronichthys cornutus	85.2
	Setipinna tenuifilis	91.8
	Takifugu niphobles	100
Mean Accuracy (Fish)		90.7
Seaweed	Cladophora wrightiana var. minor	72.5
	Ulva australis	80.0
	Padina arborescens	92.0
	Undaria pinnatifida	91.4
	Gelidium elegans	96.6
	Sargassum thunbergii	69.4
	Codium fragile	83.6
	Sargassum fusiforme	94.8
	Ishige okamurae	80.2
	Colpomenia sinuosa	97.4
Mean Accuracy (Seaweed)		85.8
Total Accuracy (Fish and Seaweed)		88.3

Table 5. Untrained image test results

Marine Species	Marine Organisms	Accuracy(%)
Fish	Odontamblyopus lacepedii	49.4
	Dictyosoma burgeri	65.23
	Pseudopleuronectes yokohamae	65.6
	Branchiostegus japonicus	90.2
	Cleisthenes pinetorum	59.4
	Ostorhinchus semilineatus	63.0
	Scomber japonicus	99.5
	Pleuronichthys cornutus	30.2
	Setipinna tenuifilis	62.4
	Takifugu niphobles	97.75
Mean Accuracy (Fish)		68.3%
Seaweed	Cladophora wrightiana var. minor	44.0
	Ulva australis	73.4
	Padina arborescens	67.8
	Undaria pinnatifida	91.2
	Gelidium elegans	70.8
	Sargassum thunbergii	79.4
	Codium fragile	57.4
	Sargassum fusiforme	67.5
	Ishige okamurae	38.0
	Colpomenia sinuosa	57.8
Mean Accuracy (Seaweed)		64.7
Total Accuracy (Fish and Seaweed)		66.5

Table 6. Normalized confusion matrix (See Appendix 1)

Marine Species	Marine Life				
	Actual Class	Predicted Class			
		Correctly classified	Accuracy	Misclassified	Accuracy
Fish	Branchiostegus japonicus	Branchiostegus japonicus	1.0		
	Cleisthenes pinetorum	Cleisthenes pinetorum	0.8	Pseudopleuronectes yokohamae	0.2
	Dictyosoma burgeri	Dictyosoma burger	0.75	Odontamblyopus lacepedii	0.25
	Odontamblyopus lacepedii	Odontamblyopus lacepedii	0.6	Branchiostegus japonicus	0.2
				Ishige okamurae	0.2
	Ostorhinchus semilineatus	Ostorhinchus semilineatus	0.75	Gelidium elegans	0.25
	Pleuronichthys cornutus	Pleuronichthys cornutus	0.4	Pseudopleuronectes yokohamae	0.6
	Pseudopleuronectes yokohamae	Pseudopleuronectes yokohamae	0.8	Cleisthenes pinetorum	0.2
	Scomber japonicus	Scomber japonicus	1.0		
	Setipinna tenuifilis	Setipinna tenuifilis	0.8	Scomber japonicus	0.2
	Takifugu niphobles	Takifugu niphobles	1.0		
Seaweed	Cladophora wrightiana var. minor	Cladophora wrightiana var. minor	0.25	Gelidium elegans	0.5
				Sargassum thunbergia	0.25
	Codium fragile	Codium fragile	0.8	Undaria pinnatifida	0.2
	Colpomenia sinuosa	Colpomenia sinuosa	0.6	Padina arborescens	0.2
				Sargassum thunbergia	0.2
	Gelidium elegans	Gelidium elegans	0.8	Ishige okamurae	0.2
	Ishige okamurae	Ishige okamurae	0.6	Gelidium elegans	0.2
				Sargassum fusiforme	0.2
	Padina arborescens	Padina arborescens	0.75	Odontamblyopus lacepedii	0.25
	Sargassum fusiforme	Sargassum fusiforme	0.75	Ulva australis	0.25
	Sargassum thunbergii	Sargassum thunbergia	0.8	Undaria pinnatifida	0.2
	Ulva australis	Ulva australis	0.8	Colpomenia sinuosa	0.2
	Undaria pinnatifida	Undaria pinnatifida	1.0		

In the graph, the cross-entropy and accuracy of the validation data were not consistent with those of the training data. This revealed an overfitting problem in the model-learning process for marine-life images. To solve this overfitting problem, we used a dropout to disable some neurons. Consequently, Fig. 6(b) confirms that the cross-entropy and accuracy of the validation data followed the cross-entropy and accuracy of the training data, thereby mitigating overfitting.

Tables 4 and 5 show the image test results with and without training. The trained image tests were randomly selected and adjusted according to the number of test data points for each marine creature. Table 4 shows the average accuracy for the selected data. Additionally, Table 5 shows the untrained test results obtained from average accuracy of the pre-segmented test data.

The trained image tests had average accuracies of 90.7 and 85.8% for fish and seaweed, respectively. Mackerel and pufferfish had the highest accuracy among fish, with 100% accuracy. Among algae, round horses had the highest accuracy, with 97.4% accuracy.

The untrained image test achieved an average accuracy of 68.3% for fish and 64.7% for seaweed. Among the fish test data, mackerel had the highest accuracy of 99.5%, whereas among the seaweed test data, the highest accuracy was 91.2%. Comparing Tables 4 and 5, the accuracy of the test image set (66.5%) is lower than that of the trained image set (85.8%).

Table 6 presents the Normalized Confusion Matrix results in tabular form. Based on the relationship between the actual and predicted classes, we analyzed the classification patterns of marine organisms and evaluated the performance of the model by determining the type and frequency of misclassification of certain marine organisms as different species.

The analysis showed that among fish species, certain classes of Branchiostegus japonicus, Scomber japonicus, and Takifugu niphobles had a classification accuracy of 1.0. However, some classes, such as Cleisthenes pinetorum, Dictyosoma burger, and Odontamblyopus lacepedii, were misclassified. In particular, Cleisthenes pinetorum had an accuracy of 0.8, whereas the remaining 0.2% were incorrectly classified as Pseudopleuronectes yokohamae. Additionally, for Pleuronichthys cornutus, Pseudopleuronectes yokohamae was misclassi-

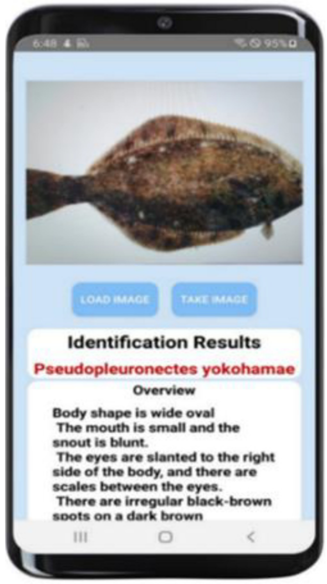


Fig. 7. Android application execution screen (See Appendix 2).

fied with an accuracy of 0.6, indicating a higher accuracy than the true class.

For seaweed species, the specific class Undaria pinnatifida had a classification accuracy of 1.0. However, some classes, such as Codium fragile, Padina arborescens, and Colpomenia sinuosa, tended to be confused with other classes. Unlike fish species, which showed an overall high classification accuracy, seaweed species had a lower classification accuracy and were more often confused with classes other than those of fish species. Cladophora wrightiana var. For the minor class, the accuracy was 0.25, indicating the lowest classification accuracy among the seaweed classes. Of these, 0.5 were misclassified as Gelidium elegans and 0.25 as Sargassum thunbergia.

Fig. 7 shows the application prediction screen implemented using the final model. When a user uses an application camera to capture marine life, the images are fed into the model, and the best matching classes are analyzed in real time, providing the user with the species name, biological characteristics, and distribution information.

V. DISCUSSION AND CONCLUSIONS

In this study, we investigated a method for recognizing Jeju marine-life images using open-source deep learning. For this purpose, the learning dataset used in the study was collected from ten species of fish and seaweed and consisted of 930 images of Jeju marine life. Preprocessing was performed on the collected image data, and all images were converted to the same resolution and color channels. After the preprocessing step, the existing CNN model was retrained using the TensorFlow framework to render it suitable for marine-life image recognition. The highest accuracy was achieved when the number of learning iterations was 100, which required approximately 43 min.

In this study, we compared the performances of three models −MobileNetV2, InceptionV3, and Xception− and selected a suitable model for marine-life classification. Additional training was performed based on the selected model to estimate its generalization ability and to adjust for overfitting. After tuning, the final model was evaluated by testing it on trained and untrained datasets. The average accuracies of the trained and untrained image datasets were 85.8 and 66.5%, respectively. Thus, we confirmed that the trained data showed a higher classification accuracy than the untrained data.

The difference in performance between the two datasets occurs because the model is over-optimized on the training data and does not generalize well to the test images. Dropout was applied to solve this overfitting problem; however, it only alleviated overfitting and did not achieve complete generalization. This is because the amount of learning data is insufficient owing to the nature of marine life, and the recognition rate decreases depending on the environment. In particular, the limited amount of training data makes it difficult for the model to sufficiently learn all possible scenarios. To address this limitation, it is essential to build a systematic class-selection system that incorporates additional training data based on generative adversarial networks (GANs) [24]. Additionally, an algorithm that can accurately distinguish marine life must be developed by analyzing the correlation between the classification within an image and the environmental context [25].

In conclusion, if a marine-life identification system is implemented through this process, it is expected that the limitations of Jeju Island's existing marine biotechnology will improve and that it will expand to various industrial fields on Jeju Island in the future [26].

ACKNOWLEDGMENTS

This research was supported by the 2024 Scientific Promotion Program funded by Jeju National University.

REFERENCES

[1] IBM, “deep learning,” [Internet], Available: https://www.ibm.com/topics/deep-learning.

[2] I. H. Sarker, “Deep learning: a comprehensive overview on techniques, taxonomy, applications and research directions,” *SN Computer Science*, vol. 2, no. 6, Aug. 2021. DOI: 10.1007/s42979-021-00815-1.

[3] T. Javaheri, M. Homayounfar, Z. Amoozgar, R. Reiazi, F.

Homayounieh, E. Abbas, A. Laali, A. R. Radmard, M. H. Gharib, S. A. J. Mousavi, O. Ghaemi, R. Babaei, H. K. Mobin, M. Hosseinzadeh, R. Jahanban-Esfahlan, K. Seidi, M. K. Kalra, G. Zhang, L. T. Chitkushev, B. Haibe-Kains, R. Malekzadeh, and R. Rawassizadeh, "CovidCTNet: an open-source deep learning approach to diagnose covid-19 using small cohort of CT images," *NPJ Digital Medicine*, vol. 4, no. 1, Feb. 2021. DOI: 10.1038/s41746-021-00399-3.

[4] Y. Yoon, J. Sang, and S. Park, "Trends of Plant Image Processing Technology," *Electronics and Telecommunications Trends*, vol. 33, no. 4, pp. 54-60, Aug. 2018. DOI: 10.22648/ETRI.2018.J.330406.

[5] J. Song, S. Lee, and A. Park, "A study on the industrial application of image recognition technology," *The Journal of the Korea Contents Association,* vol. 20, no. 7, pp. 86-96, Jul. 2020. DOI: 10.5392/JKCA.2020.20.07.086.

[6] W. Nwankwo, C. P. Nwankwo, and A. Wilfred, "Leveraging on Artificial Intelligence to Accelerate Sustainable Bioeconomy," *IUP Journal of Knowledge Management*, vol. 20, no. 2, pp. 38-59, Apr. 2022.

[7] T. Kim, (2023, June). "Jeju Island announces 'Jeju bio industry development strategy'," *Jeju Environment News* [Internet], Available: https://www.newsje.com/news/articleView.html?idxno=273624.

[8] Y. Jeon, (2023, March). "Dreaming of Jeju Bio Island, a leap forward for the marine bio industry ecosystem as a new growth engine…," *New Jejuilbo* [Internet], Available: http://www.jejuilbo. net/news/articleView.html?idxno=200555.

[9] Marine Bio-Resource Information System, Marine Life Spatial Information, [Internet], Available: https://www.mbris.kr/gis/.

[10] S. Park and J. Kim, "Red Tide Algea Image Classification using Deep Learning based Open Source," *Korean Institute of Smart Media*, vol. 7, no. 2, pp. 34-39, 2018. DOI: 10.30693/SMJ.2018.7.2.34.

[11] Marine Bio-Resource Information System, Marine Life Spatial Information, [Internet], Available: https://www.mbris.kr/gis/.

[12] S. Park and J. Kim, "Red Tide Algea Image Classification using Deep Learning based Open Source," *Korean Institute of Smart Media*, vol. 7, no. 2, pp. 34-39, May 2018. DOI: 10.30693/SMJ.2018.7.2.34.

[13] J. Park and H.-S. Yong. "Rock image classification with deep convolutional neural network based on Tensorflow," in *Korean Computer Science Conference*, pp. 1121-1123. 2018.

[14] L. Yuan, Z. Qu, Y. Zhao, H. Zhang, and Q. Nian, "A convolutional neural network based on TensorFlow for face recognition," in *2017 IEE^{E} 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, Chongqing, China, pp. 525-529, 2017, DOI: 10.1109/IAEAC.2017.8054070.

[15] M. M. Taye, "Theoretical understanding of convolutional neural network: concepts, architectures, applications, future directions," *Computation*, vol. 11, no. 3, p. 52, Mar. 2023. DOI: 10.3390/computation11030052.

[16] G. T. Adekunle and A. C. Aladeyelu. "Image Classification Of Automobiles Using Deep Learning In Tensorflow," *Image*, vol. 10, no. 3, Mar. 2023.

[17] Chollet, F. (2015). Keras [Computer software]. https://keras.io

[18] N. Mittal, D. Sharma and M. L. Joshi, "Image Sentiment Analysis Using Deep Learning," in *2018 IEEE/WIC/ACM International Conference on Web Intelligence (WI)*, Santiago, Chile, pp. 684-687, 2018 DOI: 10.1109/WI.2018.00-11.

[19] S. Sharma and S. Singh. "ISL recognition system using integrated mobile-net and transfer learning method," *Expert Systems with Applications*, vol. 221, p. 119772, Jul. 2023. DOI: 10.1016/j.eswa.2023.119772.

[20] N. Ruiz, Y. Li, V. Jampani, Y. Pritch, M. Rubinstein, and K. Aberman. "Dreambooth: Fine tuning text-to-image diffusion models for subject-driven generation," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 22500-22510, 2023.

[21] F. Cholle, "Xception: Deep learning with depthwise separable convolutions," in *Proceedings 30th IEEE Conference on Computer Vision and Pattern Recognition*, CVPR 2017, Honolulu, USA, pp. 1800-1807, 2017, DOI: 10.1109/CVPR.2017.195.

[22] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Che, "MobileNetV2: Inverted Residuals and Linear Bottlenecs," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Barcelona, Spain, pp. 4510-4520, 2018, DOI: 10.1109/CVPR.2018.00474.

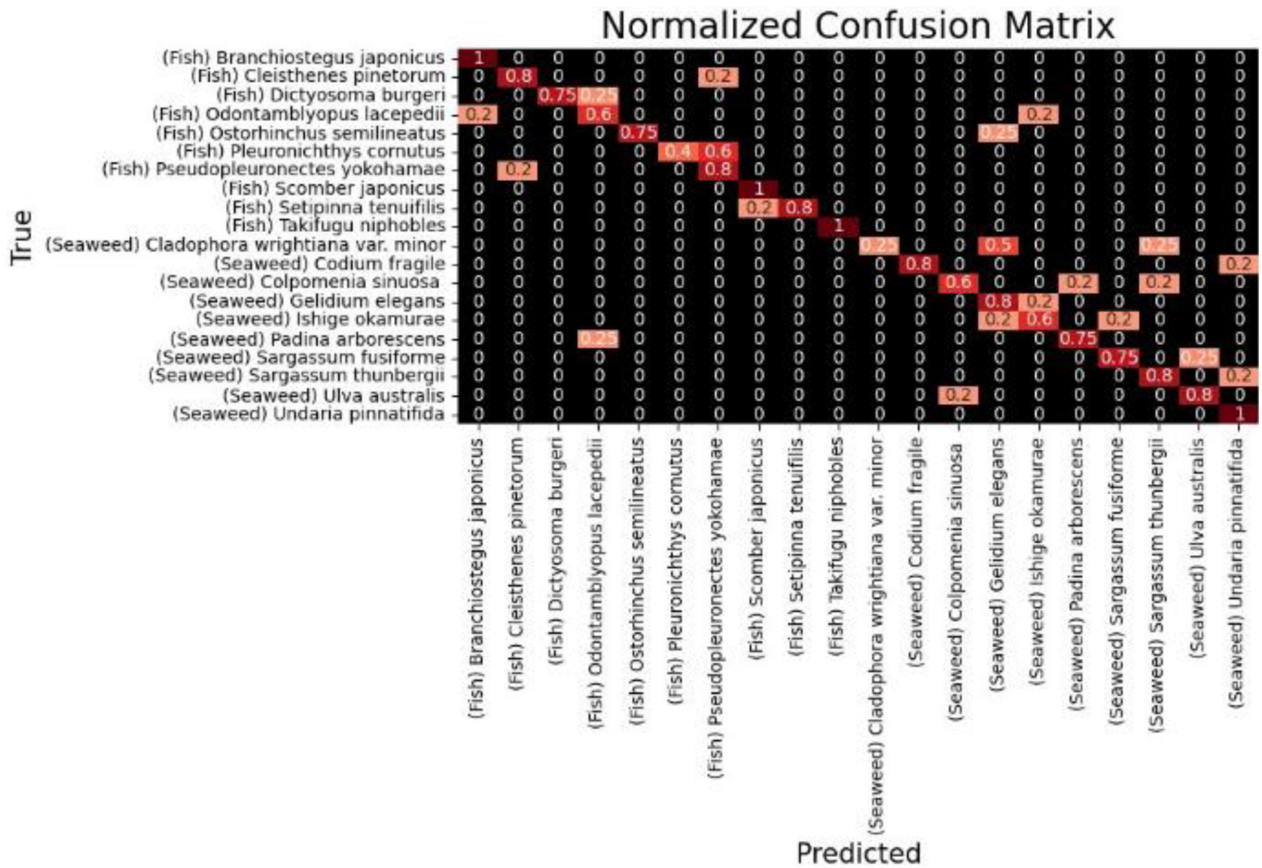
[23] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojn, "Rethinking the Inception Architecture for Computer Visin," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Las Vegas, USA, vol. 2016-December, pp. 2818–2826, 2016, DOI: 10.1109/CVPR.2016.308.

[24] A. Carreon, S. Barwey, and V. Raman, "A generative adversarial network (GAN) approach to creating synthetic flame images from experimental data," *Energy and AI*, vol. 13, p. 100238, Jul. 2023. DOI: 10.1016/j.egyai.2023.100238.

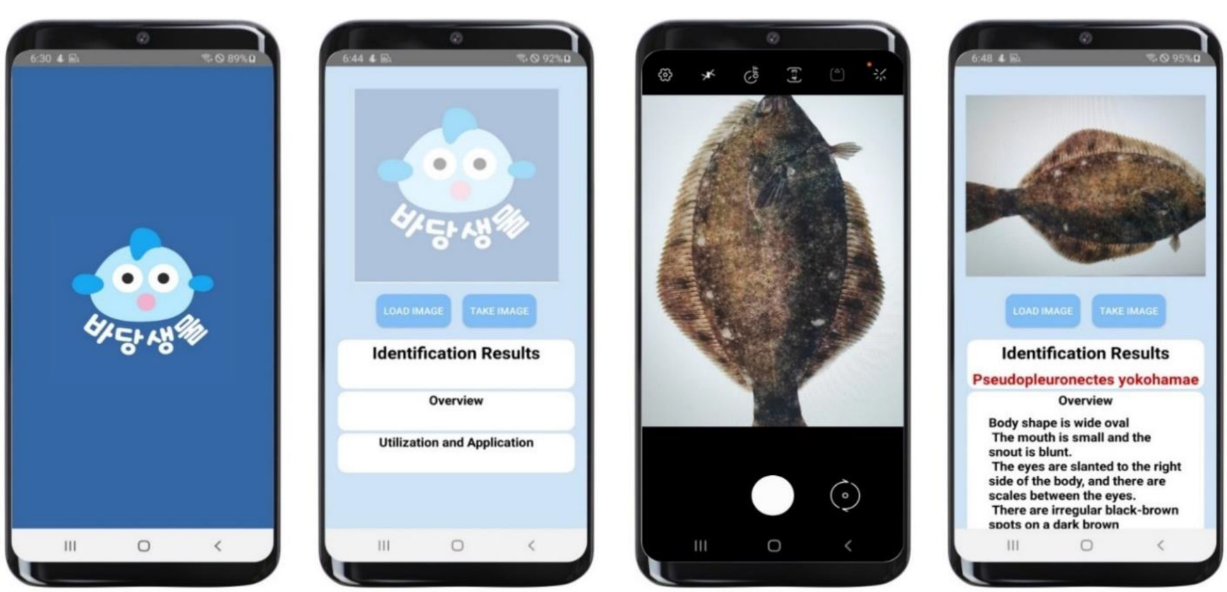
[25] S.-H. Jeong, M. Lee, and H. Yoe, "Fruit classification system using deep learning," *Journal of Bio-Environment Control,* vol. 13, no. 5, pp. 589-595, Oct. 2018. DOI: 10.34163/jkits.2018.13.5.009.

[26] K. Bezbarua and S. Goswami, "From issues to opportunities: bridging through AI for economic sustainability in Marine ecosystem," *Journal of Survey in Fisheries Sciences*, vol. 10, no. 1S, pp. 5822-5837, 2023.

APPENDIX 1. Normalized Confusion Matrix



APPENDIX 2. Android Application Screen



Jiyun Hong
has been majoring in Management Information Systems at Jeju National University, Jeju, Republic of Korea, since 2022. Her research interests include real-time video analysis utilizing artificial intelligence technology, big data analysis, and back-end development.

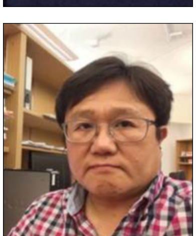
Jiwon Lee
is a fourth-year undergraduate student in Management Information Systems at Jeju National University, Republic of Korea. Her primary research focus is on image classification technology utilizing Convolutional Neural Networks (CNN).

Somin Lee
has been majoring in Management Information Systems at Jeju National University in Republic of Korea since 2022. Her main research fields include information and communication engineering and big data analysis.

Eun Ko
is a third-year undergraduate student majoring in Management Information Systems at Jeju National University in Jeju, Republic of Korea. Her academic pursuit focuses on the exploration and development of big data analysis techniques

Gyubin Kim
is a third-year student in the Department of Management Information Systems at Jeju National University, Jeju, Republic of Korea. Her main research focused on big data analysis technology for extracting meaningful conclusions from large datasets.

Jungwoon Kang
received the B.S. and M.S. degrees in Management Information Systems from Jeju National University, Jeju, Republic of Korea, in 2021 and 2022, respectively. Currently, he is a Ph.D. student in the Faculty of Data Science for Sustainable Growth at Jeju National University, Jeju, Republic of Korea. His research interests during his master's course included the application of big data in the tourism industry.



Mincheol Kim
received the Ph.D. degree in Management Science and Management Information Systems from Korea University, Republic of Korea, in 2000, and completed the Ph.D. coursework in Medical Informatics at Seoul National University, Republic of Korea, in 2004, the Ph.D. degree in Tourism (Hospitality Majors) from the University of Surrey, UK, in 2019. Currently, he is a professor in the Department of Management Information Systems at Jeju National University, Jeju, Republic of Korea. His research interests include Management Information Systems.

https://doi.org/10.56977/jicce.2024.22.3.221