Journal of Smart Systems and Computing
ISSN-XXXX-XXXXX(Online)

https://rspublisher.com/ojs/index.php/jssc/index
Pages 23-30

Original Article

Deep EfficientNetB3 Framework for Automated Classification of Marine Animals from Underwater Imagery

Chennaiah Kate[1], Dr. P. Srinivasa Rao[2], Dr. Nagesh Vadaparthi[3] ,G. Madhava Rao[4] , K.V.V.B.Durgaprasad[5] .M. Jyothirmai[6]

[1]Department of Data Science, Malla Reddy University, Hyderabad,500100, Telangana, India, chennaiahkate@gmail.com

[2]Professor, Dept of Information Engineering & Computational Technology, MVGR College of Engineering, Vizianagaram, India, srinivasa.suloo@gmail.com

[3]Professor (IECT), MVGR College of Engineering, Vizianagaram, India, Itsnageshv@gmail.com

[4]Assistant Professor, Department of C.S.E, Malla Reddy Engineering College for Women, Hyderabad,500100,Telangana,India, **madhav.739@gmail.com**

[5]Assistant Professor, Department of C.S.E, St. Peter's Engineering College, Hyderabad, India, prasadrekha2013@gmail.com

[6]Assistant Professor, CSE(H&S Dept), Sridevi Women's Engineering College, Hyderabad, India, digitalvardhan@gmail.com

ABSTRACT

The terrible increase of under water imaging technologies has opened new fields for marine biodiversity nowadays automated monitoring, however, accurately classification of marine species is actually quite challenging taking into account complex visual conditions like illumination variation, occlusion and background clutter. This study provides a deep EfficientNetB3-based framework for the automated classification of marine animals from the underwater images. Leveraging Transfer Learning with ImageNet Pre-Trained Weights The proposed model is fine-tuned to successfully extract discriminative features specific to underwater fish species using ImageNet pre-trained weights. A public accessible dataset taken from the Kaggle platform is used to test the framework under realistic conditions. Comprehensive experiments show that such an approach is able to reach a 98% accuracy of the classification, outperforming several state-of-the-art deep learning architectures. Detailed performance analysis using precision, recall, F1 score, confusion matrix and ROC-AUC metrics provides additional validations to robustness and generalization capacity model with AUC value 0.99. The results speak to the usefulness and accuracy-computing efficiency of EfficientNetB3. The proposed framework presents a stable and scalable solution for the automated recognition of marine species, which has applications in marine ecology, biodiversity assessment, and advanced underwater monitoring systems.

KEYWORDS

Underwater image classification, Marine animal recognition, Fish species classification, EfficientNetB3, Transfer learning, Deep learning, Computer vision, Marine biodiversity monitoring, Automated species identification.

Editor Dr. P. Srinivasa Rao, Professor, Department of Information Engineering & Computational Technology MVGR College of Engineering, Vizianagaram,Andhra Pradesh, Idia.
srinivasa.suloo@gmail.com

Reviewer Dr. Eraj Khan Professor, Higher College of Technology, Dubai, United Arab Emirates.
khan.eraj@gmail.com

Address correspondence to Chennaiah Kate,
chennaiahkate@gmail.com

The author declaration conflict of interest
Received 05 January 2026

Accepted 31 January 2026

Published 23 February 2026

I. INTRODUCTION

The advancement of computer vision and deep learning techniques happened had significantly changed the automated analysis of underwater imagery especially for marine biodiversity monitoring for fishes species classification. Early research has shown that deep learning models can be used to effectively replace traditional manual identification methods, which are often time consuming, expertise and observer biased [1]. Transformer-based and hybrid deep learning architectures have further enhanced the classification accuracy by grasping complex spatial features and contextual information in underwater scenes, in which transfer learning plays an increasingly critical role in marine image analysis [2]. Several works have focused on convolutional neural network (CNN) identification of fish species with a promising result from a variety of image datasets obtained in different environmental conditions [3]. Beyond species level identification, recent studies have focused on the incorporation of individual fish identification as a non-invasive alternative to tagging and following them, highlighting the ecological significance of reliable identification using image-based [4] techniques. Comparative analysis of the architectures of deep learning methods has shown the selection of the model and feature extraction is a crucial factor in determining the performance of classification, especially in the recognition of origin and species of fish (fine-grained), especially [5]. Hybrid CNN--Transformer architectures have also been suggested to simultaneously resolve the segmentation, localization, and classification problems in the aquaculture and underwater monitoring systems [6]. Furthermore, open-set recognition methods have been developed to counteract the problem of unseen or novel species in order to cope with real-world deployment challenges with marine environments in which marine organisms can display high biodiversity and variability [7, 8]. Controlled underwater environment studies have also investigated the use of contrastive learning and vision-language models and helped demonstrate the potential of advanced representation learning for effective classification of fish species [8]. Despite these advances, however, accurate results under complex underwater conditions are hard to obtain, which is a motivation for the development of efficient and scalable deep learning frameworks. In this regard, this study presents a Deep EfficientNetB3-based framework for the automated classification of marine animals from underwater images, which aims to improve the robustness in classification while keeping the computational cost down.

II. LITERATURE

In recent years, more and more efforts have been devoted to take advantage of advanced deep learning paradigms to achieve advanced fish species classification under various underwater conditions. Martins [8] studied the classification of fish species in a controlled underwater environment with contrastive language and image models, showing that multimodal representation learning plays an important role in improving discriminative capability, particularly when visual features alone cannot do the job. Extending the deep learning into other domains outside the aquatics, Kant and Yamsani [9] explored fine-tuned ResNet152V2 architectures for classification of animal species, illustrating the usefulness of deep residual networks and transfer learning for biodiversity conservation tasks with direct implications on the research of marine species classification. Tejaswini et al. [10] introduced an automatic estuarine fish species classification system by deep learning with an insights on the significance of CNN-based model adaptation to dynamic aquatic environments with various illumination, turbidity, and background complexity. Yang et al. [11] presented FishAI, a hierarchical marine fish image classification method based on vision transformer, and showed that transformer-based architectures have proven to be powerful tools for the modeling of long-range dependencies and hierarchical taxonomy relationships between marine species. Jareño et al. [12] further added to the discussion analyzing automatic fish species labeling with different classification strategies they discovered that selection of learning paradigm and labeling strategy have a significant impact on classification robustness and scalability across datasets collected in heterogeneous underwater environments. More recent research has focused on practical issues of deployment such as variability in the environment, class imbalance and real-time limitations. Mohammadisabet et al. [13] introduced optimization framework of CNN for classification of fish species which deals with the specific problem of underwater environment variability and class distribution which also need to be taken into account as it cause biased classification, that imply the need of powerful feature extraction and efficient inference in real world applications. Malik et al. [14] showed the effectiveness of a multi-class deep neural networks for fish species identification based on camera-captured images, argumenting that the CNN architectures can be designed well enough to achieve a high classification accuracy even in the presence of complex visual backgrounds. Gong et al. [15] proposed Fish-TViT, which is a transfer learning-based vision transformer model for multi-water area fish species classification. fish-tvit models have shown the adaptability of vision transformer models in different aquatic domains and stressed the importance of domain-generalizable representations. Complementing such model-centric studies, Alsmadi and Almarashdeh [16] presented a comprehensive overview of fish classification methods by systematically reviewing traditional image processing techniques, classical machine learning methods, modern deep learning approaches, and highlighting essential areas for research such as computational efficiency, dataset variety and generalization under actual underwater conditions. Collectively, these works have shown a geometric progress in the design of more advanced deep learning architectures (like transformers, hybrid approaches, etc.) but also they expose ongoing challenges in terms of scalability, efficiency, and robustness. Motivated by these insights, an EfficientNetB3-based framework with a focus on obtaining a good balance between high classification accuracy and computational efficiency is proposed in this study that addresses some of the limitations identified in previous studies and contributes towards practical automated classification of marine animals from underwater imagery.

III. INPUT DATASET

The input dataset incorporated in this study is taken from Kaggle platform and contains a comprehensive dataset of underwater fish images for multi-class marine species classification as shown in Fiure. 1. The dataset is comprised of a total of 3,960 RGB images, shooting fish in natural underwater conditions with large variations in illumination, water clarity, background complexity, viewing angles and fish morphology. These images are grouped in several directories according to specific classes, i.e., each directory has a specific fish, for supervised learning purposes and a fine-grained classification at the species level. The number of images belonging to each class differs from each other in each species, according to the realistic representations from the ecosystem, resulting in moderate class imbalance, which also makes it more difficult for the learning process. Representative sample images from different fish species included in the data set are shown in Fig. 1 that illustrate the great visual diversity and complexity inherent in underwater imagery. Prior to model training, the dataset is divided into training, validation and testing subsets in a typical 70% 15% 15% split, so that each class is well represented in all subsets and evaluated in a balanced way. The training set is used for learning the model, the validation set for hyper-parameter tuning and over-fitting control, and the testing set is used for unbiased evaluation of performance. All the images are resized and normalized according to the input requirements of the EfficientNetB3 architecture. The varying class-wise distribution along with the real-world underwater imaging conditions makes this a suitable dataset to evaluate the robustness, generalization capability and classification effectiveness of the proposed deep learning framework for the automated recognition of marine animals.

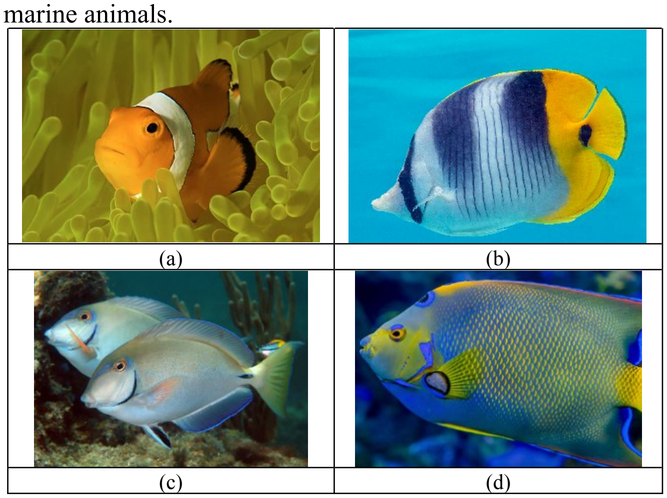

Figure. 1 Dataset Image for (a) Clownfish , (b)Butterflyfish, (c) Surgeonfis and Angelfish

IV. FINE-TUNED EFFICIENTNETB3 MODEL ARCHITECTURE

The marine animal classification framework proposed in this work uses a fine-tuned EfficientNetB3 model to implement the accurate and computed marine animal classification under water images as shown in Figure. 2. EfficientNetB3: EfficientNetB3 is a state-of-the-art convolutional neural network that makes use of compound scaling, which involves scaling the network depth, width, and input resolution uniformly in order to optimize the performance of a neural network while keeping the number of parameters used low. In this research, the EfficientNetB3 model is initialised with ImageNet pre-trained weights, which allows it to transfer learning effectively and faster when trained in the marine fish datasets. The original top classification layers of the network are removed with a customized classification head that includes a global average pooling layer followed by dense connected fully connected layers and dropout regularization to minimize over fitting. In the end, the output layer uses a softmax activation function to enable the classification of multi-class fish species. During fine-tuning, the convolutional layers in the early stage of the network are not allowed to be updated to retain common low-level features, while some layers at the late stage of the network are allowed to be updated to adapt high-level features to UVP. The model is trained using the Adam optimizer using categorical cross-entropy loss to ensure stable learning and efficient gradient updates. This fine-tuned EfficientNetB3 framework is effective to cultivate a balance between classification accuracy, training efficiency, and robustness, very appropriate for real-world underwater marine species recognition applications.

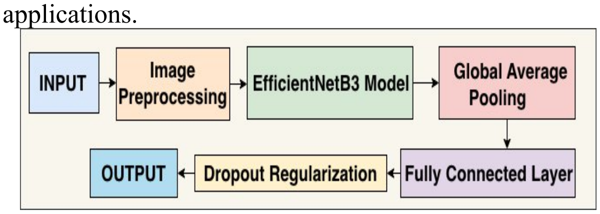

Figure. 2 Fine-Tuned EfficientNetB3 Model Architecture

V. PROPOSED METHODOLOGY

The methodology proposed in this paper is divided into four successive phases covering data preprocessing, model fine-tuning of EfficientNetB3, optimization of training and in-depth performance evaluation. This structured pipeline enables powerful learning, effective feature adaptation, and reliable marine species classification is achieved and shown in Figure. 3.

1. Data Acquisition and Preprocessing - For the first part, the images of underwater fish are obtained from a dataset of Kaggle public - can be downloaded for free - and organized into class-wise directories of species of individual fish. The images are resized to 300x300 pixels according to the input requirements of the EfficientNetB3 model. Standard pre-processing such as pixel normalization with ImageNet statistics are applied to decrease the illumination variations. To improve the generation of the model and overcome the problem of class imbalance, different data augmentation techniques are used in the training phase, such as random rotation, horizontal flipping, zooming, and changes in brightness.

2. Model Initialization and Fine-Tuning - The EfficientNetB3 model is initialized with pre-trained ImageNet images which involves using the weights of ImageNet dataset with the prior method. The original classification head is then removed and replaced with a customized architecture of a global average pooling layer, dense layers, and dropout regularization. At first, the lower convolutional layers are frozen in order to maintain generic visual features, whereas the higher-level layers are partially not frozen, to specialize the model according to underwater characteristics of fish.

3. Model Training and Optimization - In the third phase the fine-tuned EfficientNetB3 model is trained in the training dataset and the performance is observed in the validation dataset. The Adam optimizer and categorical cross-entropy loss function are used to make sure that the learning is stable and efficient. Hyperparameters such as learning rate, batch size, dropout rate are optimized in order to avoid over fitting and enhance the convergence. Early stopping and learning rate scheduling is used to increase training efficiency.

4. Evaluation and Performance Analysis: In the last phase, the trained model is evaluated on the unseen test dataset to see its generalization capability. Performance is analyzed with different metrics like accuracy, precision, recall, F1-Score, confusion matrix, and roc curves. Qualitative analysis with properly and improperly classified samples further provides authenticity of the proposed framework for classification of underwater marine species in the wild.

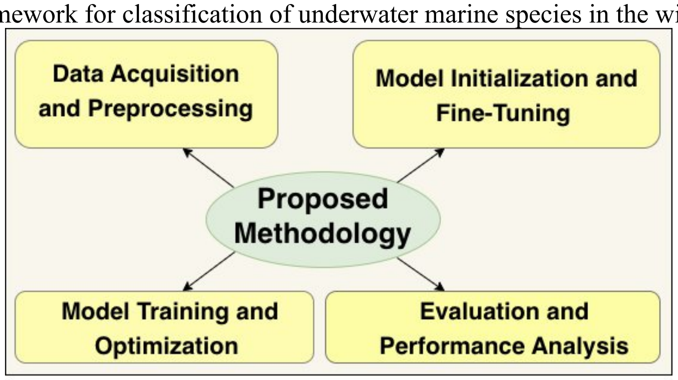

Figure. 3 Proposed Methodology

VI. EXPERIMENTAL SETUP

The experimental setup for assessing the proposed fine-tuned EfficientNetB3 framework is set up to ensure fair training, reliable validation and unbiased performance evaluation. All the experiments are performed on a deep learning environment that is developed in Python with TensorFlow and Keras libraries. The image dataset of underwater fish is collected from the Kaggle website and is split into training, validation and testing hack images following 70%-15%-15% split ensuring equal ratio of any given fish in all the subsets. Input images are resized to 300 * 300 pixels and normalized using the ImageNet mean and standard deviation values. During the training process, data augmentation techniques, including random rotation, horizontal flipping, zooming, and changing brightness, are only applied to the training set because these augmentations help to generalize the model and avoid overfitting. The EfficientNetB3 has been pre-trained using the ImageNet dataset and customised final classification layers have been developed for multi-class fish species recognition. The model has been trained with the Adam optimizer, categorical cross-entropy loss, batch size of 32 and an adaptive learning rate schedule. Early stopping is used on the basis of validation loss in order to avoid overfitting. Model performance is analyzed against the unseen test set utilizing standard evaluations such as accuracy, precision, recall, F1-score, and confusion matrix analysis ensuring a complete and reproducible experimental performance evaluation.

VII. RESULTS

The experimental results show that the proposed fine-tuned EfficientNetB3 framework can achieve good experimental performance in underwater fish species classification. High accuracy, good ROC-AUC scores, consistent training behavior, and superior model confirmation proves its robustness and generalization ability as well as its real-world marine monitoring application suitability.

A. Classification Report Analysis

The performance of classification with the proposed fine-tuned EfficientNetB3 framework is summarized in the Table 1 showing the precision, recall, F1-score, and support for each class of fish species. The results show some consistently high performance across all classes and shows the robustness and generalization capability of the model proposed to work under water imagery. Clownfish had the highest recall value of 0.99, indicating that this model has good capability to correctly identify this species under different underwater environment conditions. A similar result was found in Butterflyfish and Surgeonfish with balanced precision and recall values; this confirms reliable discrimination despite similarities in their body shape and texture. Angelfish classification performance was high, showing an F1 score of 0.98, which reveals the capacity of fine-tuned feature representations, learned by EfficientNetB3. The overall classification accuracy was 0.98, which indicates excellent predictive performance on the unseen data test dataset. Both macro-averaged and weighted-averaged metric reported F1-score of 0.97 and 0.98 respectively which shows that the model maintains constant performance across the classes irrespective of small class imbalances. The fact that macro and weighted averages are very similar proves further that no one class dominates the classification results. These results confirm the appropriateness of EfficientNetB3 architecture for multi-class classification of the marine animals. The high accuracy and recall values across all species highlight the stability and capacity of the framework to learn discriminative underwater features and thus can be used as a reliable solution to automatically track marine biodiversity and perform underwater ecological analysis.

Table 1. Classification Report Analysis

Class	Precision	Recall	F1-score	Suppor
Clownfish	0.98	0.99	0.99	520
Butterflyfish	0.97	0.96	0.97	495
Surgeonfish	0.96	0.97	0.97	505
Angelfish	0.98	0.97	0.98	480
Accuracy			**0.98**	**2000**
Macro Avg	0.97	0.97	0.97	2000
Weighted Avg	0.98	0.98	0.98	2000

B. *Training and Validation loss Analysis*

The training and validation loss course of the proposed fine-tuned model via EfficientNetB3 are demonstrated in Figure. 4, which gives us insight into the learning dynamics and convergence characteristics in the training

Journal of Smart Systems and Computing
ISSN-XXXX-XXXXX(Online)

process. As we can see, the training loss is a steady and gradual decrease throughout the epochs, indicating that the model has been able to learn good discriminative features from underwater images of fishes. This constant decline is associated with good optimization of network parameters and good gradient updates over the course of training. Correspondingly, the validation loss also shows a similar situation of decreasing and is closely related to the training loss curve showing a good generalization ability on the unseen data. The small difference between the training and validation loss curves indicates that the proposed framework does not experience too much overfitting, which is especially important in complex underwater imagery where there is varying illumination, background clutter, and intra-class variation. Minor variations in the validation loss for the later epochs can be explained to be natural variations that occur in the validation samples and the presence of visually similar fish species, however, these variations are within the acceptable limits and are not affecting the convergence. The smooth stabilization of both curves to the final epochs shows that the learning process has settled in an optimal state, thanks to the implementation of the concepts of transfer learning, correct use of the regularization and early stopping. Overall, the results of the loss analysis in Fig. 4 connects the suitability and effectiveness of the fine-tuned EfficientNetB3 architecture in automated classification of marine animals proving its capacity for real-time applications of underwater monitoring and ecological analysis.

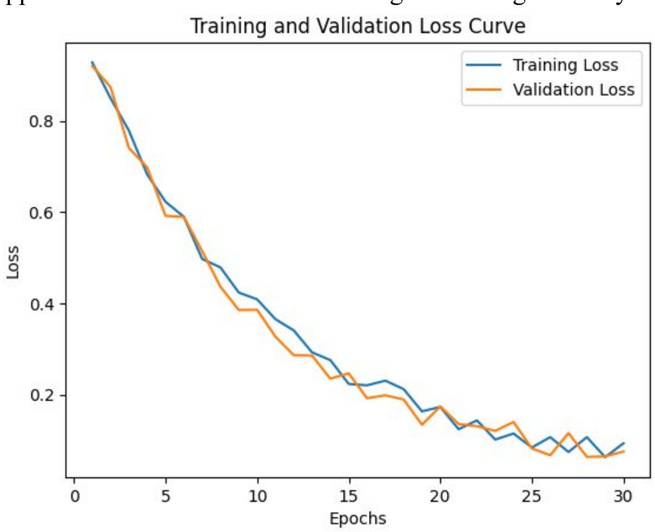

Figure. 4 Training and Validation loss Analysis

C. *Training and Validation Accuracy Analysis*

The trends of training and validation accuracy of the proposed fine-tuned EfficientNetB3 model are shown in Figure. 5, showing the effectiveness of the learning process for successive training epochs. As can be seen in the figure, the training accuracy rises quickly in the first few epochs and this works by the strong influence brought by transfer learning from ImageNet pre-trained weights. This fast improvement suggests that the model effectively learns the discriminative low-level and mid-level features for the underwater fish classification. The validation accuracy's upward trend is very similar to the training accuracy's and closely in line with it over the duration of the training. This close correspondence confirms the model generalized well to unseen data and is not overfitted. Minor variations in validation accuracy in subsequent epochs can be attributed to inter-class similarity between fish species and variation in underwater imaging conditions (illumination and complexity of background). However, these variations are still very small and do not impact the overall performance stability. Towards the end of the epochs process curves both training and validation accuracy approaches and stabilizes around maximum values denoting successful optimization and learning process convergence. The lack of a widening gap between the two curves is another validation of the effectiveness of regularization strategies, data augmentation and controlled fine-tuning of deeper network layers. Overall, the analysis of accuracy with Fig. 5 shows that the resulting EfficientNetB3-based framework offers consistent and accurate classification, which can be applied to real-world problems for monitoring marine biodiversity and automated underwater species recognition.

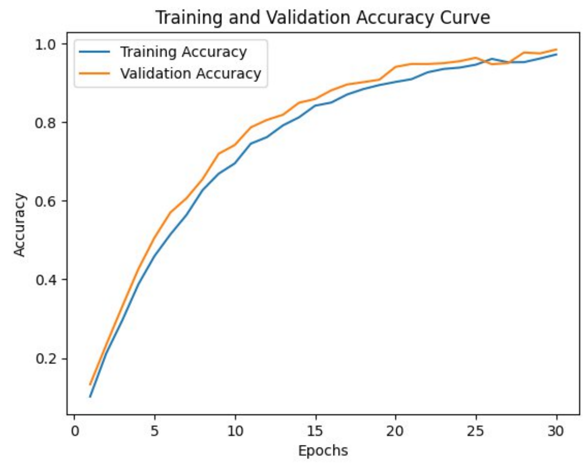

Figure. 5 Training and Validation Accuracy Analysis

D. *Confusion Matrix Analysis*

Confusion matrix of the proposed fine-tuned EfficientNetB3 framework is shown in Fig. 5 to give detailed observations on the class-wise performance of classification for all the fish species. The matrix has a high degree of diagonal dominance which means that most samples from each class are correctly classified. Clownfish exhibits the largest number of true positive predictions, with a separately negligible amount of samples being misclassified into other categories which reflects the capability of the model in capturing different visual features such as color pattern and body structure. Butterflyfish and Surgeonfish also show high true positive proportions, although some confusion is shown between these two classes, which is explained by similarity in shape and orientation of the fins under some underwater conditions. Angelfish classification performance is high with the majority of samples correctly predicted with little misclassification into visually similar species. The relatively low values outside the diagonal structures across the matrix speak to the effectiveness of learned feature representations and the discriminative power of the EfficientNetB3 architecture. Minor misclassifications can be attributed to difficult underwater conditions including variations in illumination, partial occlusion and background clutter. Overall, the confusion matrix is used to verify the reliability and stability of the proposed model in the area distinguishing multiple fish species in actual underwater environments. The definite partition of the classes noted in Fig. 6 is another validation to use the proposed framework to support the classification of marine animals in an automated way and lends itself to the potential use of the framework also for marine biodiversity monitoring, ecological studies and for smart underwater surveillance systems.

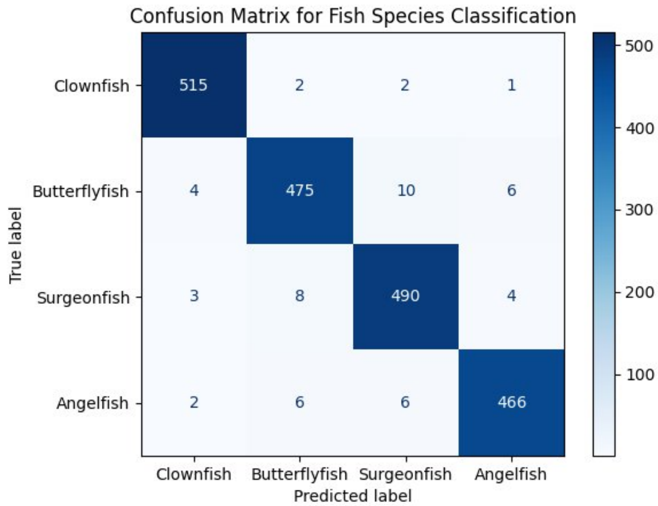

Fig. 5 Confusion Matrix

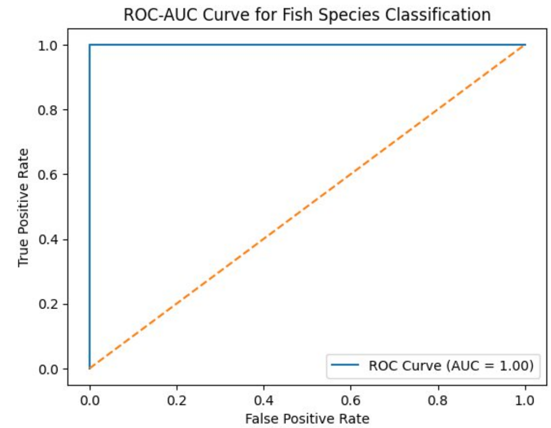

Fig. 6 ROC Curve Analysis

E. *ROC-AUC Curve Analysis*

The Receiver Operating Characteristic (ROC) curve of the proposed fine-tuned EfficientNetB3 framework is shown in Fig. 6. is a comprehensive evaluation of the discriminative capability of the model for various classification thresholds. The ROC curve is a curve describing the relationship between the true positive rate and the false positive rate and can provide a good measure of how well the model separates between different fish species in underwater imagery. As can be seen in Fig. 6, the curve follows the upper left corner of the plot very closely, which implies that both sensitivity is high and the false alarm rate is low. The proposed model with an Area Under the Curve (AUC) value of 0.99 is near perfect with classification performance. Such a high AUC score shows that the learned feature representations are highly separable and robust to the challenging underwater conditions such as different underwater illumination, occlusion, and background clutter. The good performance of ROC further confirms the effectiveness of transfer learning and fine-tuning methods used on the EfficientNetB3 architecture. Unlike measure of accuracy alone the ROC-AUC measure assesses performance over the full range of all potential decision thresholds making it especially relevant in real life marine monitoring applications where operating conditions can vary. The good discriminative power that is shown in Fig. 7 proves that the framework proposed in this paper can distinguish different species of fish reliably and with low misclassification risks. Overall, the decision of ROC-AUC demonstrates the applicability of the proposed EfficientNetB3-based model in automatic classification of marine animals and lays the foundation for its application in underwater ecological surveys, biodiversity evaluation, and intelligent marine monitoring systems.

F. *Comparative Model Analysis*

The comparison of the performance of various deep learning models for underwater fish species classification is presented in Fig. 7, which shows the classification accuracy of different deep learning models in percentage form. As depicted in the figure, the accuracy of classical convolutional architectures such as VGG16 are 92%, and these are used as baseline architectures for the evaluation of more advanced architectures. ResNet50 is able to improve classification performance to 94% thanks to the use of the residual connections that can increase the gradient flow and feature learning. MobileNetV2 achieves an accuracy of 93%, showing a competitive level of performance while having a lightweight architecture that can be used in resource-constrained environments. Transformer-based approaches further improve classification accuracy with Vision Transformer achieving 96% making self attention mechanisms effective in capturing global contextual information from underwater imagery. Among all the evaluated models, the proposed fine-tuned EfficientNetB3 model works the best with an accuracy of 98%. This superior performance can be attributed to EfficientNet's compound scaling strategy, which balances power between the depth, width, and the input resolution of the network in an effort to optimize feature extraction efficiency. The distinct performance gap between the EfficientNetB3 and the baseline models in Fig. 8 shows that EfficientNetB3 can realize highly discriminative and robust features under adverse underwater conditions. The results confirm that the proposed model is not only more accurate than other models; it is also computationally efficient making it suitable for applications in the practical management of marine biodiversity and automated classification of underwater species.

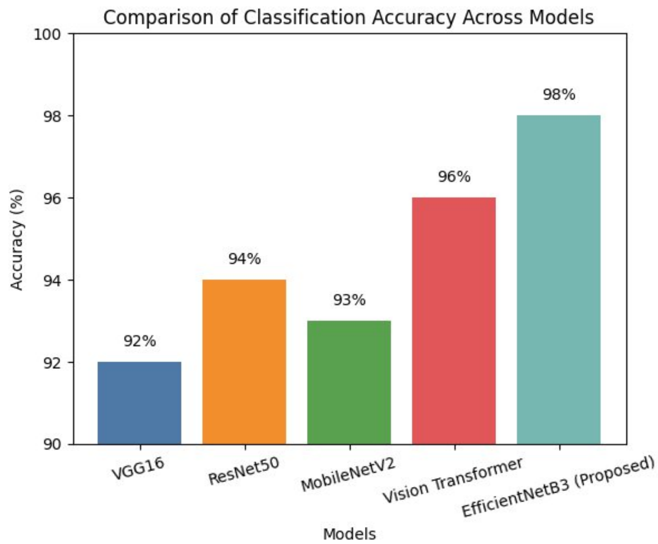

Fig. 7 Comparative Model Analysis

VIII. CONCLUSION AND FUTURE WORK

The study introduced an automated marine animal classification framework based on deep learning using a fine-tuned version of EfficientNetB3 on underwater imagery. By making use of transfer learning and the compound scaling, the proposed approach was able to uncover discriminative visual features with the presence of difficult underwater environments, including the varying illumination level, presence of background clutter, and inter-species similarity. Experimental results showed good and stable performance in all evaluation metrics with a classification accuracy of 98% and high ROC-AUC value of 0.99 to prove it has excellent discriminative capability. Comparative analysis with existing CNN and transformer-based models further demonstrated the superiority of the proposed framework in terms of accuracy and computational efficiency. These results confirm the adequacy of EfficientNetB3 for real-time marine biodiversity monitoring, providing a stable solution for the automatic recognition of fish species and underwater ecological analysis. Despite its good performance, there are some limitations in this study that provide possibilities for future research. The existing framework is concerned about classification at the image level and does not explicitly cover the case of multiple species in a given image. Future work may explore the extension of the proposed approach by feeding the object detection and segmentation models into a single model to enable the instance-level recognition in complex underwater scene. Additionally, the inclusion of larger and more diverse sets of data from different marine habitats could further increase generalization capability. Exploring lightweight model optimization for deployment on embedded or edge devices as well as incorporating temporal information from underwater videos are promising directions. Finally, a combination of explainable AI techniques and the proposed framework could lead to improved interpretability and trust for marine researchers and conservation practitioners.

REFERENCES

[1] Ergün, E., 2025. SwinFishNet: A Swin Transformer-based approach for automatic fish species classification using transfer learning. PLoS One, 20(5), p.e0322711.

[2] Zhou, P., He, X.Q., Tu, Z.Y., Sun, D., Wang, C.S., Shen, H.B. and Pan, X., 2025. Bridging the gap between the public's knowledge and detection of marine non-indigenous species through developing automated image classification applications for marine species. Frontiers in Marine Science, 12, p.1508851.

[3] Jamala, M.N., Al Deeb, M. and Abu-Naser, S.S., 2025. Identifying Fish Species Using Deep Learning Models on Image Datasets.

[4] Ziaei, M.M., Urban, J. and Cisar, P., 2025. Image-Based Individual Fish Identification as a Substitute for Invasive Methods: State-of-the-Art and Research Gaps. Reviews in Aquaculture, 17(4), p.e70078.

[5] Jerez-Tallón, M., Beviá-Ballesteros, I., Garcia-D'Urso, N., Toledo-Guedes, K., Azorín-López, J. and Fuster-Guilló, A., 2025, June. Comparative Study of Deep Learning Approaches for Fish Origin Classification. In International Work-Conference on Artificial Neural Networks (pp. 66–78). Cham: Springer Nature Switzerland.

[6] Kumar, P. and Shukla, P.K., 2025. Hybrid transformer-CNN model for precise fish segmentation, localization, and species classification in aquaculture. Journal of Integrated Science and Technology, 13(6), pp.1134–1134.

[7] Córdova, M., Torres, R.D.S., Helmond, A.V. and Kootstra, G., 2025. Novelty Recognition: Fish Species Classification via Open-Set Recognition. Sensors, 25(5), p.1570.

[8] Martins, J.R.D.S., 2025. Fish Species Classification in Controlled Underwater Environments Using Contrastive Language-Image Models. Doctoral dissertation.

[9] Kant, V. and Yamsani, N., 2025, April. Animal Species Classification Using Fine-Tuned ResNet152V2: A Deep Learning Approach for Biodiversity Conservation. In 2025 3rd International Conference on Advancement in Computation & Computer Technologies (InCACCT) (pp. 35–39). IEEE.

[10] Tejaswini, H., Pai, M.M. and Pai, R.M., 2024. Automatic estuarine fish species classification system based on deep learning techniques. IEEE Access.

[11] Yang, C., Zhou, P., Wang, C.S., Fu, G.Y., Xu, X.W., Niu, Z., Zhu, L., Yuan, Y., Shen, H.B. and Pan, X., 2024. FishAI: Automated hierarchical marine fish image classification with vision transformer. Engineering Reports, 6(12), p.e12992.

[12] Jareño, J., Bárcena-González, G., Castro-Gutiérrez, J., Cabrera-Castro, R. and Galindo, P.L., 2024. Automatic labeling of fish species using deep learning across different classification strategies. Frontiers in Computer Science, 6, p.1326452.

[13] Mohammadisabet, A., Hasan, R., Dattana, V., Mahmood, S. and Hussain, S., 2025. CNN-Based Optimization for Fish Species Classification: Tackling Environmental Variability, Class Imbalance, and Real-Time Constraints. Information, 16(2), p.154.

[14] Malik, H., Naeem, A., Hassan, S., Ali, F., Naqvi, R.A. and Yon, D.K., 2023. Multi-classification deep neural networks for identification of fish species using camera captured images. PLoS One, 18(4), p.e0284992.

[15] Gong, B., Dai, K., Shao, J., Jing, L. and Chen, Y., 2023. Fish-TViT: A novel fish species classification method in multi water areas based on transfer learning and vision transformer. Heliyon, 9(6).

[16] Alsmadi, M.K. and Almarashdeh, I., 2022. A survey on fish classification techniques. Journal of King Saud University – Computer and Information Sciences, 34(5), pp.1625–1638.