Classification of Marine Organisms Using Deep Learning Method

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***Abstract*—In last two decades, the automatic classification of marine species based on images has been considered as one of the best approach. In fact, oceans are complex ecosystems, difficult to access, and often the images obtained are of low quality, in particular deep ocean images. In such scenario, classification using traditional methods becomes tedious. Therefore, the enhancement or pre-processing techniques to the images before applying classification algorithms is an essential task. In this work, we propose an image enhancement and classification pipeline that allows automated processing of images from benthic moving platforms.**

I. Introduction

The utilization of Machine Learning (ML) techniques within the realm of Artificial Intelligence (AI) has witnessed a consistent expansion across various scientific domains, including but not limited to medicine, agriculture, industry, and marine ecology. In recent years, the application of AI-based algorithms for tracking and classifying marine organisms in benthic realms has experienced remarkable growth, facilitated by advancements in data collection technologies such as cabled observatories, Remotely Operated Vehicles (ROVs), and Autonomous Underwater Vehicles (AUVs). Despite these advancements, challenges persist in marine imaging acquisition, primarily due to the hostile and variable nature of the ocean environment, which poses obstacles such as low visibility, fluctuating lighting conditions, floating particles, and data scarcity.

Data Scarcity:

The availability of comprehensive datasets for training machine learning models in marine species classification remains limited. This scarcity of data poses a significant challenge, as ML algorithms require large amounts of labeled data to effectively learn and generalize patterns from the input data.

Image Quality Challenges:

Underwater imaging encounters various quality challenges, including low visibility, fluctuating lighting conditions, and the presence of floating particles. These factors degrade image quality, making it difficult for algorithms to accurately detect and classify marine organisms. Effective pre-processing techniques are essential to mitigate these challenges and improve the overall quality of the images used for classification tasks.

The quality of underwater images poses significant challenges for the accurate detection and classification of marine species, necessitating effective pre-processing techniques [20]. While high-definition imaging technologies have enhanced image quality, environmental variability in real-world scenarios demands sophisticated pre-processing methods to improve detection accuracy. Both Computer Vision (CV) and Deep Learning (DL) methods play vital roles in image enhancement, encompassing tasks such as noise removal, contrast adjustment, and color correction. However, manual processing of the vast datasets collected from marine environments is impractical, underscoring the need for automated processes to manage and enhance these datasets effectively. Despite efforts to establish automated pipelines for image treatment in certain operational scenarios, such as cabled observatories, similar initiatives are lacking for mobile platforms like IOVs [21]. Addressing these challenges requires innovative approaches that leverage machine learning algorithms to improve image quality, facilitate species detection, and enhance classification accuracy in marine ecosystems.

II. Proposed Methodology

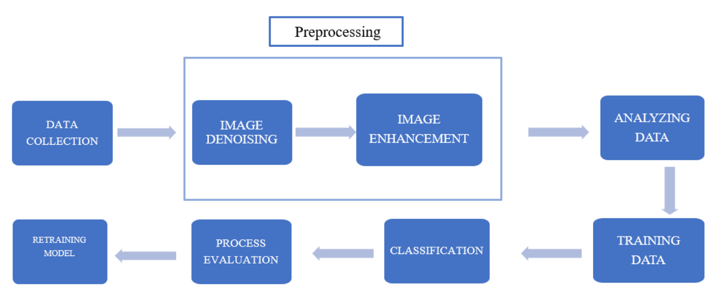

Fig. 1: Methodology

A. *Data Collection*

Group of Species:

- The Black Sea Sprat (*Sprattus sprattus*) is a small pelagic fish found in the Black Sea and adjacent waters. It is characterized by its silvery coloration and slender body, often forming large shoals near the surface of the water [22].
- The Gilt-Head Bream (*Sparus aurata*) is a demersal fish commonly found in the Mediterranean Sea and along the coasts of Europe and Africa. It is known for its distinctive golden spot on the head, and its silver-grey body with pinkish hues [36].
- The Horse Mackerel (*Trachurus trachurus*) is a pelagic fish species inhabiting the Atlantic Ocean, Mediterranean Sea, and adjacent waters. It has a streamlined body, metallic blue-green dorsally, and silver-white ventrally, with vertical stripes along its sides [37].
- The Red Mullet (*Mullus barbatus*) is a demersal fish found in the Mediterranean Sea, Black Sea, and eastern Atlantic Ocean. It is characterized by its reddish body, large eyes, and prominent barbels on its chin [38].
- The Red Sea Bream (*Pagrus pagrus*) is a demersal fish species inhabiting the Mediterranean Sea, Black Sea, and eastern Atlantic Ocean. It has a reddish-pink body, with yellowish fins and distinctive black markings near its eyes [39].
- The Sea Bass (*Dicentrarchus labrax*) is a highly prized marine fish found in the eastern Atlantic Ocean, Mediterranean Sea, and Black Sea. It has a sleek, elongated body, silver-grey in color, with dark vertical bars along its sides [40]
- Shrimp are small, decapod crustaceans found in marine environments worldwide. They are characterized by their elongated bodies, with ten legs, and a curved, slender abdomen. Shrimp exhibit a variety of colors and patterns depending on the species [41].
- The Striped Red Mullet (*Mullus surmuletus*) is a demersal fish species distributed throughout the Mediterranean Sea and eastern Atlantic Ocean. It has a reddish-pink body with distinctive longitudinal stripes along its sides [42].
- Trout are freshwater fish belonging to the Salmonidae family, widely distributed across North America, Europe, and Asia. They have a streamlined body, olive-green to brownish in color, with a speckled pattern along their sides [43].

B. Data Preprocessing

Preprocessing is important for machine learning because it cleans the data by handling missing values, outliers and errors. It balances and balances the variety, ensuring equal scale for effective teaching. Feature engineering improves model performance by creating or modifying features. Dimensionality reduction techniques such as PCA reduce complexity and reduce overfitting [6]. Categorical variables are included in calculations for algorithm compatibility. Normalization of distributions ensures the efficiency of certain algorithms. Data imbalance can be addressed by oversampling, undersampling, or artificial sample generation. Preprocessing reduces computational cost by reducing redundant information. Prepare data for efficient model learning and generalization of unseen data. Finally, preprocessing is essential to generate accurate and reliable machine learning models.

The Preprocessing techniques we used are :

1) Gaussian Noise:
Gaussian noise is a type of random noise added to images, following a Gaussian distribution, which affects the pixel intensity values, introducing randomness and altering image clarity [23].
2) Random Contrast and Brightness:
Random contrast and brightness adjustments involve modifying the contrast and brightness levels of an image randomly, aiming to enhance or diminish the visual impact of the image while preserving its essential features [24]
3) Image Filter Utils:
Image Filter Utils refer to a set of tools or functions designed to apply various filters and transformations to images, such as blurring, sharpening, or edge detection, aiding in image enhancement and processing tasks [25].
4) Image Filter UnsharpMask:
Image Filter UnsharpMask is a technique used to sharpen images by creating a mask of the image's edges, enhancing contrast along these edges to improve overall image clarity and definition [26].

Fig. 2: Raw Image Before Preprocessing [34]

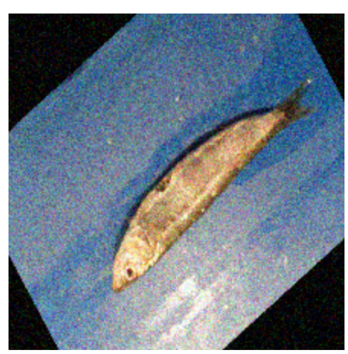

Fig. 3: Adding Gaussian Noise

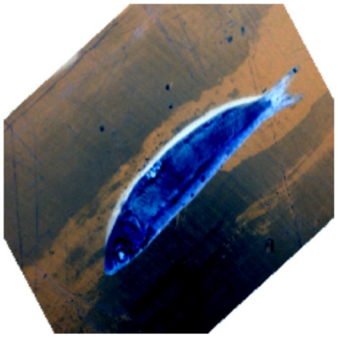

Fig. 4: Using Random Contrast and Brightness

Fig. 5: Using ImageNet Utils

Fig. 6: Using Imagenet UnsharpMask

C. *Data Augmentation*

Data Augmentation is a common technique used to artificially increase the size of a dataset by generating new, modified versions of existing data samples [9]. This process involves applying various transformations such as rotation, flipping, scaling, cropping, or adding noise to images, thereby creating diverse versions of the same image.

Fig. 7: Raw Image [34]

Fig. 8: Augmented Images

By utilizing data augmentation, even with limited original data, we can generate additional samples to enhance model training and improve its robustness [9]. This augmentation strategy enables a more comprehensive exploration of the data space and can lead to better generalization performance in machine learning models.

III. Model Proposed

A. *Feedforward Neural Network (FNN)*

Feedforward Neural Networks (FNN) is a type of neural network where information flows in one direction, from input to output, without any cycles, facilitating tasks like pattern recognition and regression analysis. FNNs consist of interconnected layers of nodes, each layer processing information before passing it to the next layer, enabling complex computations for various machine learing tasks.

1) The model begins with a flattened input layer, converting an image with a shape of(224,224,3) into a flat vector.
2) Following the input layer, there are three dense layers with ReLU activation functions(512,256 and 128 neurons each), introducing non-linearity.
3) A dropout layer with a rate of 0.5 is added after the first dense layer, randomly deactivating 50% of connections during training to enhance generalization and prevent overfitting.
4) The output layer has as many neurons as classes (9) with softmax activation for multi-class classification.

After training and testing the Feedforward Neural Network(FNN), it achieved an accuracy of 60%.

B. *Convolutional Neural Network (CNN)*

Convolutional Neural Networks (CNN) are specialized architectures for image and spatial data processing. They use convolutional layers with filters to extract hierarchical features from input images. CNNs are highly effective in tasks such as image recognition, object detection, and computer vision due to their ability to capture spatial patterns [27].

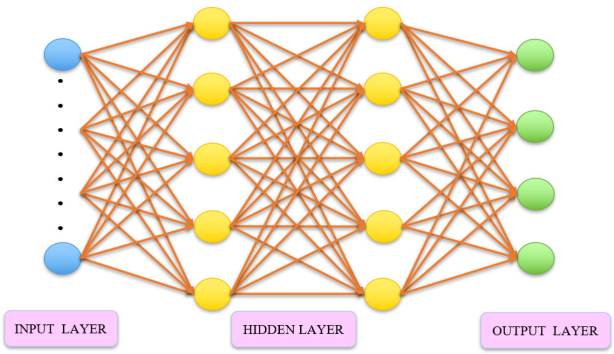

Fig. 9: FNN Architechture

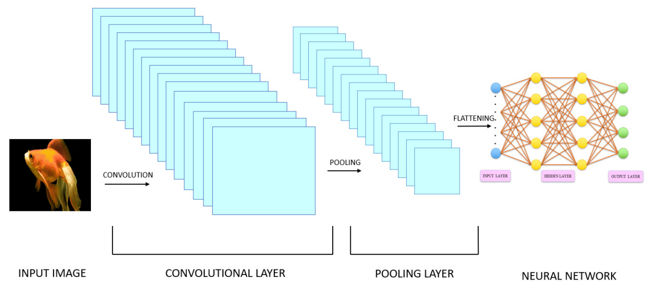

Fig. 10: CNN Architecture [32]

1) Convolutional Layer :
   - Teaches filters or kernels convolve with the input image, creating feature maps.
   - Multiple filters capture diverse visual aspects, enhancing the network's ability to recognize complex patterns.
2) Pooling Layer :
   - Downsamples feature maps by selecting representative values.
   - Common operations include max pooling and average pooling.
3) Flattening :
   - Final feature maps are flattened into a 1-dimensional vector to serve as input for fully connected layers.
4) Training :
   - CNN is trained on a labeled dataset, minimizing a loss function to optimize filter and layer weights.
   - Backpropagation and gradient descent are employed for weight adjustments during training [27].
5) Prediction :
   - Trained CNN predicts on new data by passing it through network layers.
   - Final layer's output represents predicted class probabilities or regression values.
6) Softmax Layer :
   - Produces probability distributions over classes, aiding in multi-class classification.
   - Normalizes input logits into probabilities using the softmax function, facilitating confident predictions.

C. *Comparisons of Different Models*

1) AlexNet
   - AlexNet comprises convolutional and max-pooling layers for feature extraction, followed by fully connected layers. ReLU activation introduces non-linearity, and techniques like local response normalization and dropout enhance generalization.
   - After training and testing it achieved an accuracy of 50%.
2) DenseNet
   - DenseNet utilizes dense connectivity, where each layer receives input from all preceding layers, promoting feature reuse. Dense blocks concatenate feature maps for intricate representations with fewer parameters, interspersed with transition layers for efficiency.
   - After training and testing it achieved an accuracy of 74.23%.
3) VGGNet
   - VGGNet features a simple, uniform architecture with stacked 3x3 convolutional layers and max-pooling for down sampling. Small filters with stride 1 capture detailed spatial information effectively, while fully connected layers process high-level features for prediction.
   - After training and testing it achieved an accuracy of 98.33%.
4) MobileNet
   MobileNet employs depthwise separable convolutions to reduce computational complexity while maintaining accuracy. Depthwise convolutions process each input channel separately, significantly reducing computational cost. Pointwise convolutions combine outputs from depthwise convolutions, allowing for cross-channel interaction and further parameter reduction. MobileNet architectures typically include depthwise separable convolutions stacked with pointwise convolutions and use techniques like linear bottlenecks for efficiency. There are three verisons which are as follows:
   a) MobileNet
      - Employs depthwise separable convolutions for efficiency, reducing computational cost while preserving accuracy. It achieves this by decomposing standard convolutions into depthwise and pointwise convolutions. MobileNet architectures are well-suited for mobile and embedded vision applications due to their lightweight nature.
      - After training and testing it achieved an accuracy of 99.2%.
   b) MobileNetV2
      - MobileNetV2 builds upon the original MobileNet architecture, introducing inverted residual blocks

and linear bottlenecks for improved performance. It emphasizes feature reuse and efficiency, making it suitable for resource-constrained environments. MobileNetV2 achieves higher accuracy with lower computational cost compared to its predecessor.
- After training and testing it achieved an accuracy of 99.4%.

c) MobileNetV3 Small
- MobileNetV3 Small is a compact version of MobileNetV3, optimized for mobile and edge devices with limited computational resources. It introduces efficient inverted residuals with squeeze-and-excitation blocks for improved feature representation and attention mechanisms. MobileNetV3 Small maintains high accuracy while minimizing model size and computational complexity.
- After training and testing it achieved an accuracy of 98%.

TABLE I: ACCURACY SCORES OF CNN ARCHITECTURES

S No.	CNN Architecture	Accuracy Score
1	AlexNet	50%
2	DenseNet	74.23%
3	VGGNet	98.33%
4	MobileNet	99.2%
5	MobileNetV2	99.4%
6	MobileNetV3 Small	98%

IV. Observations

A. *Definitions of Evaluation Metrics*

1) Accuracy Score:
- Accuracy measures the overall correctness of the model's predictions by calculating the ratio of correctly predicted instances to the total instances.

$$Accuracy = \frac{NumberofCorrectPredictions}{TotalNumberofPrediction}$$

- Higher accuracy indicates that the model is making more correct prediction overall.

2) Precision Score:
- Precision quantifies the accuracy of the positive class predictions. It calculates the ratio of true positive predictions to the total predicted positives.

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives}$$

- Precision is crucial when the cost of false positives is high. Higher precision means fewer false positives.

3) Recall Score:
- Recall measures the model's ability to identify all relevant instances, particularly the positive instances. It calculates the ratio of true positive predictions to the total actual positives.

$$Recall = \frac{TruePositives}{TruePositives + FalseNegatives}$$

- Recall is vital when missing positive instances can have significant consequences. Higher recall indicates fewer false negatives.

4) F1 score:
- F1 Score is the harmonic mean of precision and recall, providing a balanced measure between the two metrics.

$$F1Score = \frac{2 \times (Precision \times Recall)}{Precision + Recall}$$

- F1 Score considers both false positives and false negatives, making it a useful metric when class distributed is imbalanced.

B. *Process*

*1) **Concatenation**:* Concatenation of images in machine learning involves combining multiple images into a single image along a specific axis, such as horizontally or vertically [44]. It is commonly used for data augmentation to increase the dataset size. Concatenating images can also facilitate multi-channel inputs, where different types of images are treated as channels of a single input, providing comprehensive information to the model. In Siamese networks, pairs of images are concatenated along the channel axis to compute similarity metrics. It enables multi-modal learning by combining images with other data types like text or numerical features. Concatenating images can aid feature extraction by capturing relationships or patterns across the images. However, its effectiveness depends on the task requirements and the model architecture. Overall, concatenation offers flexibility in data representation and can enhance model performance across various tasks [44].Here in this process we got an accuracy of 98%.

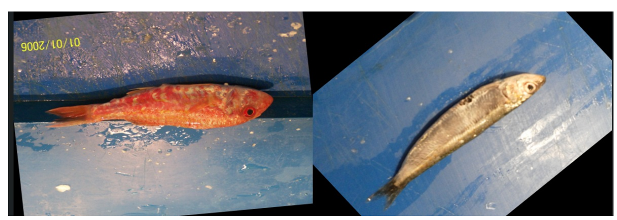

Fig. 11: Concatenated Images [34]

*2) **Incomplete Images**:* Incomplete images in machine learning refer to images that are missing certain parts or are partially obscured. Dealing with such images is crucial for robust performance in tasks like object recognition or segmentation. Techniques like image inpainting or completion algorithms are used to fill in missing regions, enabling models to process and analyze incomplete images effectively. Addressing incomplete images ensures model robustness and

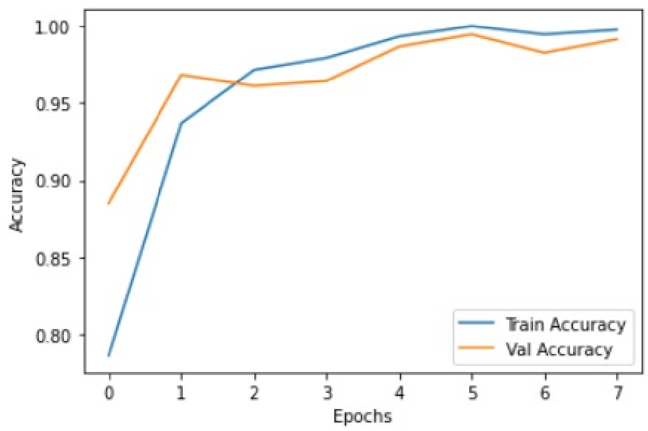

Fig. 12: Accuracy Function

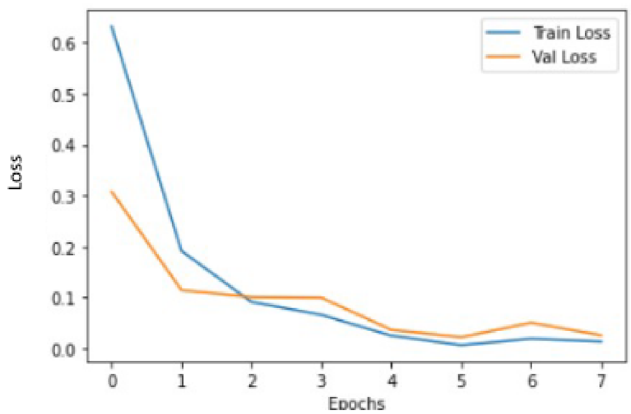

Fig. 13: Loss Function

TABLE II: ACCURACY SCORES

S No.	Score Type	Score
1	Accuracy Score	96.55
2	F1 Score	96.54
3	Precision Score	96.75
4	Recall Score	96.55

reliability in real-world scenarios [18]. The accuracy we got by using this Incomplete image technique is 96%

TABLE III: ACCURACY SCORES

S No.	Score Type	Score
1	Accuracy Score	96.79%
2	F1 Score	96.79%
3	Precision Score	96.83%
4	Recall Score	96.79%

Fig. 14: Incomplete Image [34]

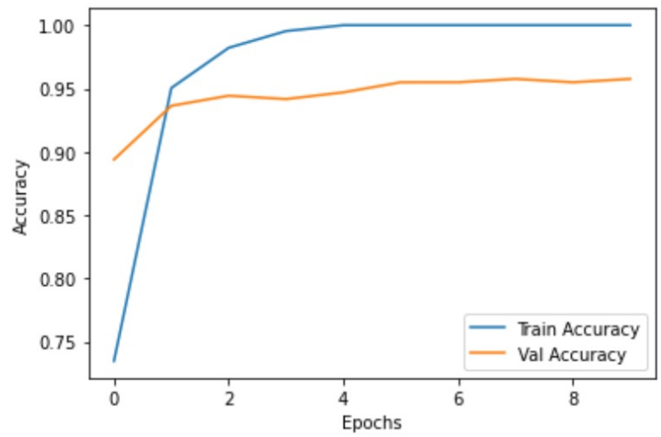

Fig. 15: Accuracy Function

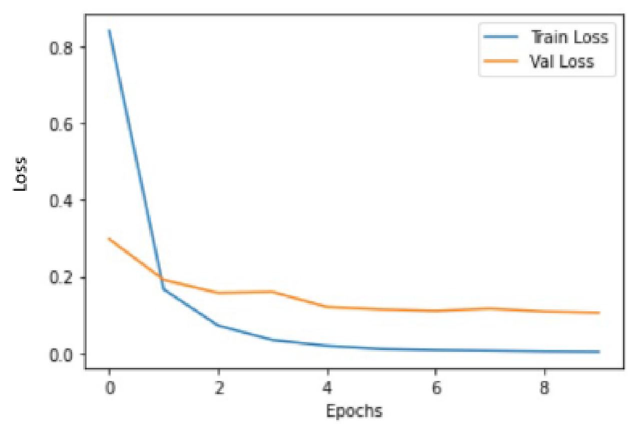

Fig. 16: Loss Function

*3) **Overlapping Images:*** Overlapping images in machine learning offer benefits such as enhanced data augmentation, crucial for training models with limited data. They aid in localization and object detection tasks by ensuring comprehensive coverage of objects or regions of interest. In semantic segmentation, overlapping patches enable accurate delineation of object boundaries across different parts of the image. Additionally, they bolster the model's robustness to translations and shifts in input data, improving generalization.They support ensemble learning approaches by generating diverse training samples for improved model performance.Here,Accuracy is 93% .

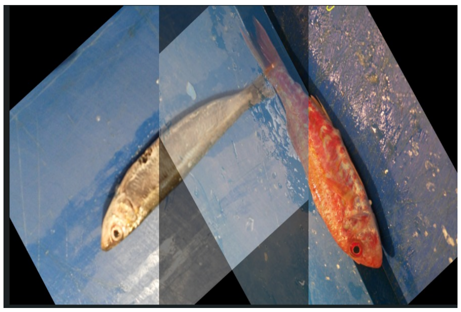

Fig. 17: Overlapping Image [34]

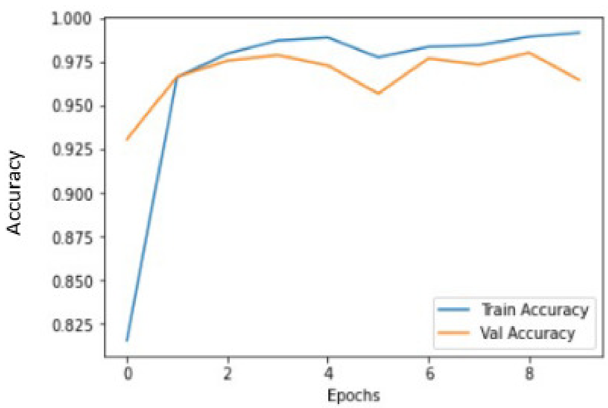

Fig. 18: Accuracy Function

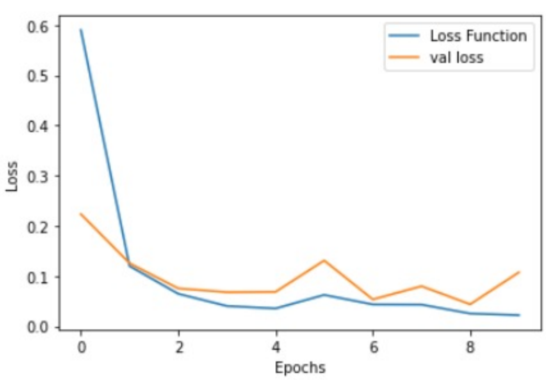

Fig. 19: Loss Function

*4) **Gray Scaling**:* Grayscale conversion is often employed as a preprocessing step to simplify image data. This conversion reduces the dimensionality of the data by transforming RGB (Red, Green, Blue) images into single-channel grayscale images, where each pixel value represents the luminance of the corresponding pixel in the original image.

TABLE IV: ACCURACY SCORES

S No.	Score Type	Score
1	Accuracy Score	96.76%
2	F1 Score	97.96%
3	Precision Score	98.09%
4	Recall Score	97.96%

Fig. 20: Gray Image [34]

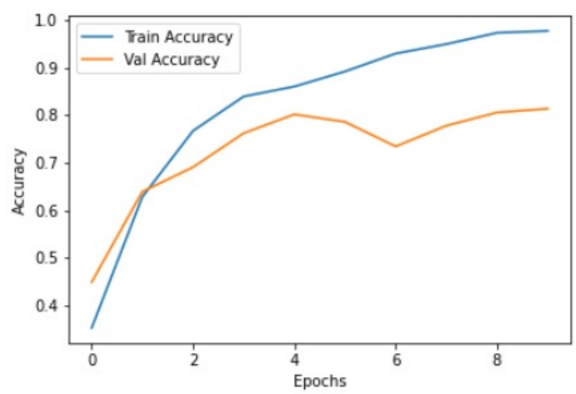

Fig. 21: Accuracy Function

TABLE V: ACCURACY SCORES

S No.	Score Type	Score
1	Accuracy Score	96.67%
2	F1 Score	96.68%
3	Precision Score	96.71%
4	Recall Score	96.67%

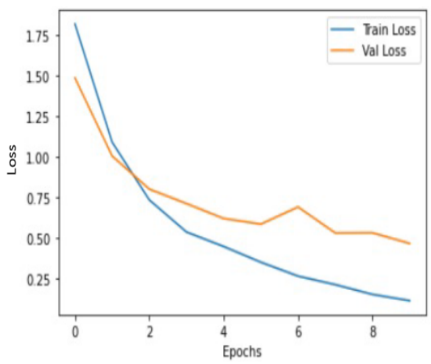

Fig. 22: Loss Function

TABLE VI: COMPARISON OF ACCURACY SCORES OF COLOUR IMAGES AND GRAY SCALE IMAGES

S No.	Colour Images	Colour Images	Gray Scale Images
1	Concatenated Images	96.76%	50%
2	Incomplete Images	74.23%	74.23%
3	Overlapping Images	98.33%	98.33%

CONCLUSION

It aims to classify fish species using Convolutional Neural Network (CNN) and MobileNet v2 models. The CNN model along with MobileNet v2 model achieved a respectable accuracy of 99.2%.

We faced challenges throughout the project. Notably, when two classes were combined in the same image, the accuracy dropped to 98%. Additionally, incomplete images posed a challenge, resulting in an accuracy of 95%. Additionally, overlay images posed challenges, resulting in an accuracy of 93%. Accuracy decreased to 81% when grayscale images were used. Furthermore, when the images were divided into 23 groups, the accuracy was 93% using CNN.

Despite these challenges, our work represents a significant advance in the classification and identification of marine ecosystems. By using advanced machine learning techniques, we have gained valuable insights into the distribution of marine ecosystems, paving the way for future marine research and conservation efforts in biology.

ACKNOWLEDGMENT

We gratefully acknowledge the support and resources provided by the National Institute of Technology, Goa throughout the course of this research. Our sincere appreciation goes to NIT, Goa for fostering an environment conducive to academic exploration and learning.

REFERENCES

[1] Benfield MC, Grosjean P, Culverhouse PF, Irigoien X, Sieracki ME and Lopez-Urrutia A, "Research on Automated Plankton Identification ", . *Oceanogr. 2007*, 20, pp.172-87, Dec.2007.

[2] Yajuan Wei, "Study of Zooplankton Automatic Recognition Method for Dark Field Image," *Ocean University of China*, 2013

[3] Frederic Maussang; Liyun Guelton; Rene Garello; Alexis Chevallier, "Marine life observation using classification algorithms on ocean surface photographs" *OCEANS 2015 - Genova*, Genova, Italy, 1547-3457, 2015.

[4] Hongwei Qin, Xiu Li, Jian Liang , Yigang Peng and Changshui Zhang, "DeepFish: Accurate Underwater Live Fish Recognition with a Deep Architecture," *Neurocomputing*, 2015.

[5] Christian Szegedy, Wei Liu, Yangqing Jia, et al, "Going deeper with convolutions," *Proceedings of the 2015 IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1-9, 2015.

[6] A. I. Kukharenko and A. S. Konushin, "Simultaneous classification of several features of a person's appearance using a deep convolutional neural network," *Pattern Recognition and Image Analysis*, vol. 25, pp. 461-465, 2015.

[7] HooChang Shin, Roth, Holger Roth, Mingchen Gao and Ronald M Summers, "Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning," *IEEE Transactions on Medical Imaging* vol. 35, pp. 1285- 1298, 2016.

[8] Tajbakhsh Nima, Shin JaeY, Gurudu, Suryakanth R and et al, "Convolutional Neural Networks for Medical Image Analysis: Fine Tuning or Full Training?" *IEEE Transactions on Medical Imaging*, vol. 35, pp. 1299-1312, 2016.

[9] horten, C., Khoshgoftaar, T.M," A survey on Image Data Augmentation for Deep Learning.",*J Big Data*,6, 60 (2019).

[10] Keqing Zhu, Jie Tian and Haining Huang, "Underwater object Images Classification Based on convolutional neural network," *2018 IEEE 3rd International Conference on Signal and Image Processing (ICSIP)*, pp. 301-305, 2018.

[11] I. Fedorov, R. P. Adams, M. Mattina, and P. Whatmough, "SpArSe: Sparse architecture search for CNNs on resource-constrained" in Proc. Adv. Neural Inf. Process. Syst., vol. 32,pp. 1–13, 2019.

[12] M.Vimal Raj and S. Sakthivel Murugan, "Underwater Image Classification using Machine Learning Technique", *2019 International Symposium on Ocean Technology (SYMPOL)*,Ernakulam,India 1939-2811, 2019.

[13] Hafez Ahmad ,"MACHINE LEARNING APPLICATIONS IN OCEANOGRAPHY", *Aquatic Research*, University of Chittagong,Bangladesh,161-169,2019.

[14] Lian Xu, Mohammed Bennamoun, Senjian An, Ferdous Sohel and Farid Boussaid , "Deep Learning for Marine Species Recognition" *Smart Innovation, Systems and Technologies book series* ,Volume 136,2019.

[15] Alessandra Lumini and Loris Nann, "Deep Learning and transfer learning fea- tures for plankton classification" *Ecological Informatics*, 33-43, 2019.

[16] R Mitra, TM Marchitto, Q Ge, B Zhong, B Kanakiya, MS Cook, JS Fehrenbacher, JD Ortiz, A Tripatiand E Lobaton, "Automated species-level identification of planktic foraminifera using convolutional neural networks, with comparison to human performance", *Elsevier*, 2019.

[17] Kaichang Cheng and Mark C.Benfield "Enhanced CNN for Plankton identification and enumeration",*IEEE Conference*,021-9570,2019.

[18] Mahsa Valizadeh and Sarah Jeannette Wolff,"Convolutional Neural Network applications in additive manufac turing",*Elsevier B.V*,2022.

[19] Ranran Lou, Zhihan Lv, Shuping Dang, Tianyun Su and Xinfang Li , "Application of machine learning in ocean data", *Sensors*, 22, no.21: 8436, 2022.

[20] Sparsh Mittal , Srishti Srivastava , J Phani Jayanth , "A Survey of Deep Learning Techniques for Underwater Image Classification", *IEEE Acess*, 13140, 2021.

[21] Vanesa Lopez-Vazquez ,Jose Manuel Lopez-Guede, Damianos Chatzievangelou , Jacopo Aguzzi , "Deep learning based deep-sea automatic image enhancement and animal species classification", *Metrics*,Article number: 37 (2023), 2023.

[22] LEONORI, I., TIČINA, V., GIANNOULAKI, M., HATTAB, T., IGLESIAS, M., BONANNO, A., COSTANTINI, I., CANDUCI, G., MACHIAS, A., VENTERO, A., SOMARAKIS, S., TSAGARAKIS, K., BOGNER, D., BARRA, M., BASILONE, G., GENOVESE, S., JURETIĆ, T., GAŠPAREVIĆ, D., DE FELICE, "History of hydroacoustic surveys of small pelagic fish species in the European Mediterranean Sea", *Mediterranean Marine Science*,22(4), 751–768. https://doi.org/10.12681/mms.26001

[23] Ameen Mohammed Abd Al-salam Selami , Ahmed Freidoon Fadhil , "A Study of the Effects of Gaussian Noise on Image Features", *Kirkuk University Journal / Scientific Studies* ,2016.

[24] Maurya, Lalit ,Lohchab, Viney. Mahapatra, Prasant , Abonyi, János , "Contrast and brightness balance in image enhancement using Cuckoo Search-optimized image fusion", *Journal of King Saud University*,2021.

[25] T. A. Mahmoud , S. Marshall, “Edge-Detected Guided Morphological Filter for Image Sharpening”, *EURASIP Journal on Image and Video Processing*,Article ID 970353 , Volume 2008.
[26] Ameen, Zohair, Muttar,Alaa,Badrani, Ghofran , “Improving the Sharpness of Digital Image Using an Amended Unsharp Mask Filter”, *International Journal of Image, Graphics and Signal Processing*,2019.
[27] Yamashita, R., Nishio, M., Do, R.K.G. et al. , “Convolutional neural networks: an overview and application in radiology.”, *Insights Imaging*,9, 611–629 (2018).
[28] Vishal Rajput, *Ultimate Neural Network Programming with Python*. USA: Prentice-Hall, Inc., 2023.
[29] Derrick Mwiti, *Deep learning with TensorFlow and Keras*. 2022.
[30] https://www.kaggle.com/datasets/slavkoprytula/aquarium-data-cots
[31] http://f4k.dieei.unict.it/datasets/bkg_modeling/
[32] https://github.com/mousecpn/Collection-of-Underwater-Object-Detection-Dataset
[33] https://github.com/xinzhichao/Underwater_Datasets
[34] https://www.kaggle.com/datasets/vencerlanz09/sea-animals-image-dataste/data
[35] https://github.com/soroushj/python-opencv-numpy-example/blob/master/unsharpmask.py
[36] https://www.fao.org/fishery/docs/CDrom/aquaculture/I1129m/file/en/en_giltheadseabr.htm
[37] https://www.fishbase.se/summary/trachurus-trachurus
[38] https://www.fishbase.se/summary/mullus-barbatus.html
[39] https://www.fao.org/3/ap922e/ap922e.pdf
[40] https://www.fishbase.se/summary/dicentrarchus-labrax.html
[41] https://www.britannica.com/animal/shrimp-crustacean
[42] https://www.fishbase.se/summary/mullus-surmuletus.html
[43] https://alburyestatefisheries.co.uk/trout-facts
[44] https://www.geeksforgeeks.org/concatenate-images-using-opencv-in-python/