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Marine Animal Classification Using Deep Learning and Convolutional Neural Networks (CNN)

Md Shariar Rahman Oion*, Moinul Islam†, Farhana Amir‡, Md. Emon Ali§, Mosraful Habib¶, Md. Saddam Hossain‖, and Md. Anwar Hussen Wadud**
Department of Computer Science and Engineering
Bangladesh University of Business and Technology, Dhaka, Bangladesh
Email: shariaroion05@gmail.com*, moinul180180@gmail.com†, farhanaamir2000@gmail.com‡, emonali.w@gmail.com§, mosrafulhabib21@gmail.com¶, mhossain@bubt.edu.bd‖, mwadud@bubt.edu.bd**

***Abstract*—The development of artificial intelligence greatly helps in this challenging task of classifying different species of marine animals based on their visual characteristics. Using Convolutional Neural Networks (CNN), this study developed an accurate and efficient method to classify marine animals. The project adopted a systematic approach, from data collection and preprocessing to building a CNN architecture, training the model, and deploying it for performance evaluation and real-time forecasting. The task at hand is to collect a variety of photos of marine animals and prepare them by compressing and flattening the pixel values. Convolutional, pooling, and fully connected layers contribute to the architecture of the CNN model. The dataset is used to train the model, and the hyperparameters are tuned for the best results. The completion of this research highlights the achievement of its goals, including the creation of a reliable CNN-based model for classifying marine fauna. The trained model has excellent accuracy when identifying and classifying different species of marine animals and has an accuracy of 87.99%. The performance of this model has been further improved and will help our proposed models and educational programs to increase its capabilities. Overall, this experiment demonstrates the effectiveness of CNNs in marine animal classification and emphasizes the potential for further development in the area. This research helps us understand and conserve marine ecosystems and supports a number of scientific, conservation, and educational initiatives by precisely identifying and classifying marine animal species.**

***Index Terms*—Artificial Intelligence, Marine Animal, Deep Learning, Convolutional Neural Networks, Convolutional Layers.**

I. Introduction

A wide variety of marine life, including a great variety of intriguing marine creatures, can be found throughout the oceans of the Earth [1]. For many scientific, ecological, and conservation purposes, accurate identification and classification of these animals is crucial. To address this challenge, automated systems utilizing cutting-edge technology like deep learning and convolutional neural networks (CNNs) [2], [3] offers a potential solution. Deep learning's ability to learn intricate patterns directly from raw data, along with CNNs' effectiveness in image classification through capturing local spatial relationships, holds great promise in revolutionizing the discipline of marine animal classification [4], [5]. This research aims to create an automated deep learning and CNN-based system capable of accurately detecting and categorizing marine animals by leveraging large annotated datasets. The goal is to achieve high levels of accuracy and effectiveness in classifying marine animals, ultimately contributing to the understanding and conservation of marine ecosystems [6].

This research focuses on developing an automated deep learning and CNN-based system for classifying marine animals accurately. Utilizing large datasets of annotated marine animal photos, the proposed method will train a CNN model [7] capable of detecting and categorizing distinct species. This research aims to overcome the challenges of manual identification and the limitations of conventional methods by harnessing the power of deep learning techniques [8]. The thesis addresses crucial research problems, including defining the ideal CNN architecture for classifying marine animals, collecting and preprocessing identified marine animal photos to create a diverse training dataset, and evaluating the system's performance compared to other approaches. The ultimate goal is to showcase the system's potential for managing marine ecosystems, supporting conservation activities, and advancing scientific research in marine biology and ecology [9].

The necessity for precise and effective identification and classification of marine species is the background issue in the thesis article on marine animal classification using deep learning and Convolutional Neural Networks (CNN) [10], [11]. The manual observation and subjective judgment that is frequently used in traditional ways of classifying marine animals can be time-consuming, prone to mistakes, and have a finite ability to scale. As a result, the challenge backdrop emphasizes the necessity of creating a solid deep learning-based system that can successfully categorize marine species based on their visual traits [12]. The system should be able to handle the difficulties brought on by changes in appearance and environmental factors while also taking into account the constraints of data accessibility [13]. The goal is to increase the precision and effectiveness of marine animal classification in order to help scientists, conservationists, and other interested parties better comprehend and protect marine ecosystems. The motivation behind this work is to provide scientists, environmentalists, and policymakers with an automated and standardized tool to enhance marine habitat research and conservation efforts [14]. It aims to make contributions in creating a unique deep learning architecture and dataset, applying transfer learning, evaluating different models, analyzing interpretability, and deploying the system for real-world use [15].

The main contributions of this research

- Dataset creation of a unique deep learning architecture.
- Transfer learning for marine animal classification comparative evaluation of different deep learning models.
- Analysis of interpretability and explainability.
- Deployment and evaluation in real-world scenarios.

The introduction of our system discusses the system's motivation, objective, and contribution. The article is set up as follows: Section 2 explores the existing literature review on marine Animal Classification Using Deep Learning and CNN. We provide an in-depth analysis of our methodology model in Section 3. In Section 4, result analysis, Use our model to the dataset we choose and compare our results to existing models. Section 5, we draw a conclusion from our research, model, and overall experience of our research

II. LITERATURE REVIEW

Abdullah et al. [16] proposed three cutting-edge object identification models, YOLOv3, YOLOv4, and YOLOv5, in order to identify and categorize algal species. The study collected microscopic images, preprocessed the data, and used DC-GAN for data augmentation. YOLOv5 emerges as the top-performing model, demonstrating high accuracy and inference speed. The proposed model, combining DC-GAN and YOLOv5, exhibits robustness and efficiency in real-time identifying Algae. If such models were combined with drones or microcontrollers, harmful algal blooms might potentially be monitored in real-time. Future research directions included expanding the dataset, incorporating more real-world images, and exploring alternative models for improved precision.

Cui et al. [17] presented a literature review on fish detection using a neural network model. The authors addressed challenges such as limited training data and overfitting by employing data augmentation and the dropout algorithm. They also refined a CNN model's loss function and other parameters to enhance fish detection in real-world conditions, including blurry ocean water. The system's focus on embedded systems for AUV design and optimizations further contributes to the field. Overall, this literature review highlighted the significance of the authors' contributions to dataset establishment, algorithm improvements, and practical applicability. Song et al. [18] presented a novel approach for Object recognition and case separation of underwater creatures using the Mask R-CNN framework. By incorporating the MSRCR enhancement algorithm, the proposed method achieved improved accuracy compared to conventional methods (SIFT) and popular deep learning models (SSD, YOLOv3, Mask R-CNN). This study also shows that deep learning models may benefit from appropriate photo-enhancing methods applied to underwater scenes, even with little training data. However, the method's practical application was challenging due to its low speed and limited suitability for long-distance object recognition underwater.

Jalal et al. [19] introduced automated fish identification and categorization using YOLO: a novel approach, a machine learning approach [11], [20]. It improved performance in harsh underwater environments by using data motion inspired by GMM and optical flow algorithms. The system achieved promising results on benchmark datasets, outperforming existing methods. Although it required more computational power, advanced microprocessors and GPUs enabled near real-time performance.

Salman et al. [21] presented the categorization of fish species using a CNN deep architecture [22], including two standard datasets. The authors demonstrated superior performance compared to other recent approaches, establishing their method as the best reported for the given datasets. Future work aims to enhance the CNN architecture through the development of a better loss function. The authors also suggested comparing the performance of several deep architectures for identifying and classifying fish species, focusing on unconstrained underwater environments and exploring the potential benefits of incorporating color information into the CNN training process.

Lumini et al. [23] addressed the challenging task of underwater imagery analysis for plankton and coral classification. The authors proposed an ensemble approach that combines fine-tuned convolutional neural network (CNN) models trained with different strategies. They evaluated the performance of various CNN models on multiple datasets and find DenseNet to be the best standalone model. However, the ensemble of multiple CNNs achieved significantly higher performance. To reduce complexity, the authors employ feature selection [24], resulting in a lighter ensemble with only 11 classifiers, outperforming other ensemble methods.

Monirujjaman et al. [25] presented a survey of current deep-learning techniques for finding and categorizing marine items beneath the water. The methods were organized by their detection objectives, and a summary of the features and deep learning architectures used by each method was provided. While deep learning has been extensively studied for coral identification and classification, less attention has been paid to seagrass despite its importance to the marine environment. The article emphasized the need to integrate color and texture-based data, and it proposed that a hybrid approach including both hand-crafted features and neural networks could be most effective for seagrass identification and classification.

Xu et al. [26] provided deep-learning techniques applied to marine species recognition. The focus was on image classification, which serves as the foundation for other visual tasks and the creation of marine species distribution maps. This chapter analyzes the pros and cons of deep and handmade features in the context of feature extraction and combination approaches specific to marine species. The specific difficulties of marine data, such as color deterioration and morphological differences, were also taken into account when researchers investigated the recognition of marine species in movies.

Mana et al. [27] presented a comprehensive deep learning-based method for detecting and classifying temperate fish species. The authors use YOLOv3 for reliable fish recognition in a wide range of challenging environments, with an average accuracy of 86.96%. When used for fish classification, the CNN-SENet architecture achieved a state-of-the-art accuracy of 99.27% on the Fish4Knowledge dataset without any data augmentation or visual pre-processing. The approach proved successful in real-time analysis of underwater videos, demonstrating its potential to alleviate the workload of scientists studying underwater ecosystems. However, the lower accuracy for temperate fish (83.68%) is attributed to the relatively lower dataset and significant variation in image data.

Gray et al. [28] produced a marine animal image classification using transfer learning, and different models reveal promising results. The experiment compared three models: MobileNetV1, MobileNetV2, and an undisclosed third model [29]. The MobileNetV2 model achieved the highest validation set accuracy of 92.89%, indicating its effectiveness in classification task. Although MobileNetV1 had the fastest average classification time, MobileNetV2 only had a negligible 0.001-second difference, making it a suitable choice for real-time classification. Additionally, the compact size of approximately 40 MB makes MobileNetV2 ideal for embedded devices.

The literature evaluation on classifying marine animals with deep learning and convolutional neural networks (CNN) showed a thorough awareness of the area's body of work. Numerous research studies have demonstrated how well deep learning methods, notably CNNs, perform when correctly categorizing and identifying marine species from visual data. These techniques have shown encouraging outcomes in terms of accuracy, robustness, and scalability.

III. METHODOLOGY

The CNN architecture, which is built to extract pertinent features from the photos of marine animals efficiently, is the foundation of the suggested framework [30]. Many convolutional layers, followed by a pooling layer and, lastly a fully connected layer, make up the architecture. In order to capture spatial patterns and features at varying scales, the convolutional layers use a wide variety of filters. The pooling layers reduce the number of dimensions while maintaining the essential data. Fig. 1 Based on input photos, the proposed system seeks to identify and categorize diverse types of marine animals precisely. The system is made up of a number of important parts, each of which is essential to completing the overall classification assignment.

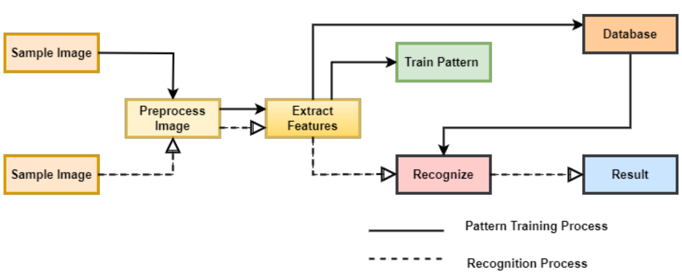

Fig. 1: System Architecture

A. Data Gathering and Prepossessing

The system starts by gathering a large dataset made up of captioned photos of various marine species. This collection contains several species that range widely in size, shape, and color. The gathered images are preprocessed to normalize their size, eliminate noise, and improve essential attributes to enable efficient training.

B. Convolutional Neural Network

A deep learning model built on a CNN architecture serves as the system's main building block. The CNN is in charge of studying and tripping the supplied photos of their identifying features [31]. Full-connected, pooling, and convolutional layers are only some of its numerous elements, which together allow the model to comprehend and categorize the visual patterns unique to various marine animals.

C. Training and Validation

The CNN model is trained on the preprocessed dataset using a supervised learning strategy. Through iterative forward and backward propagation, the model gains the ability to optimize its internal parameters during the training phase. [32] The network is fed batches of images during training, and the weights are updated after computing the loss. In order to monitor the model's correctness and guard against overfitting, its performance is assessed using a different validation dataset

D. Testing and Evaluation

After the CNN model has been trained, it is tested using an independent testing dataset. The system uses input from unseen photos and the trained model to determine the associated species of marine animal [33]. The predictions are compared to the actual labels to determine how well the classification system performed in terms of accuracy, precision, recall, and F1-score.

IV. RESULT ANALYSIS

This chapter includes the experimental setup to evaluate the system. The evaluation graphs and numbers are also denoted in the following sections.

A. Dataset

The sea-creature dataset in Table 1 we use for classifying marine animals contains a dataset size of 312 mb and a number of classes of 23. Train-df can handle up to 1332 files at once. Any train-df course necessitates a total of 290 files. The train is 9597 meters long Size Confirmation: 2057 A valid df is at least 2057 characters long, has an average height and width of 228 and 286 pixels wide and tall, and has an aspect ratio of 0.797.

TABLE I: Dataset Table

Animals	The Truth	Num. Of Data	Data Processing
Clams	100%	497/497	496680.75files/s%
Coral	100%	500/500	456200.13files/s
Crab	100%	499/499	463649.21files/s
Dolphin	100%	782/782	467162.19files/s
Eel	100%	497/497	470345.01files/s
Jelly Fish	100%	845/845	467447.49files/s
Lobster	100%	499/499	55318.03files/s
Octopus	100%	562/562	410948.20files/s
Shrimp	100%	488/488	439892.62files/s
Squid	100%	483/483	424172.70files/s
Starfish	100%	499/499	160791.79files/s
Seal	100%	414/414	452316.19files/s
Seehorse	100%	478/478	412271.71files/s
Whale	100%	572/572	171858.30files/s

B. Training Procedure

Train the CNN model on the dataset SGD or Adam should be used to train the CNN model on the dataset. Fig. 2 The model adjusts its weights during training to minimize the difference between projected class probabilities and ground truth labels. Forward propagation transmits images via the network. For better interpretation, Grad-Cam heatmaps are generated

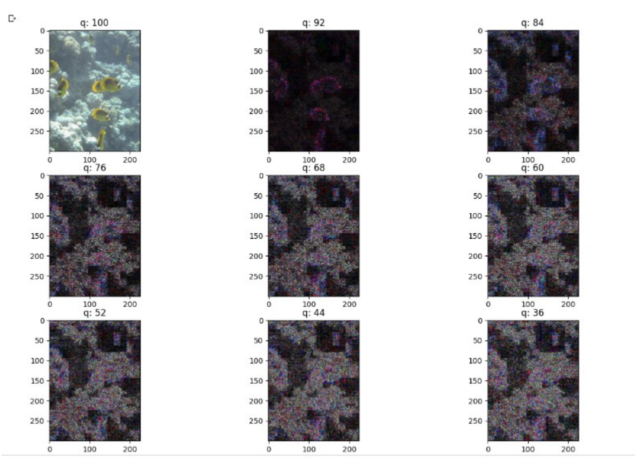

Fig. 2: Random Training Data

for selected images. These heatmaps highlight regions of the image that strongly influence the model's predictions By visualizing these regions, we gain insight into the features the model focuses on for classification.

C. Evaluation

To assess the precision and generalizability of the trained model, it is crucial to evaluate its performance on the testing set. This may be evaluated using many different metrics, including accuracy, precision, recall, and F1-score. The accuracy with which the algorithm assigns categories to marine species may be gauged using these criteria. [34]

Precision measures how well a model is able to detect positive occurrences and is expressed as the percentage of positive cases that were properly predicted relative to the total number of positive examples. Precision = TP / (TP+ FP)

Recall, sometimes referred to as sensitivity or true positive rate, measures how accurately a model can identify positive cases. It is the percentage of positive cases out of all positive cases that have been correctly expected.

Recall= TP / (TP + FN).

The F1-score is a single metric that strikes a good compromise between accuracy and recall since it is the harmonic mean of these two metrics. When the dataset is skewed, accuracy and recall must be balanced.

F1-score = 2 * ((Precision * Sensitivity) / (Precision + Sensitivity))

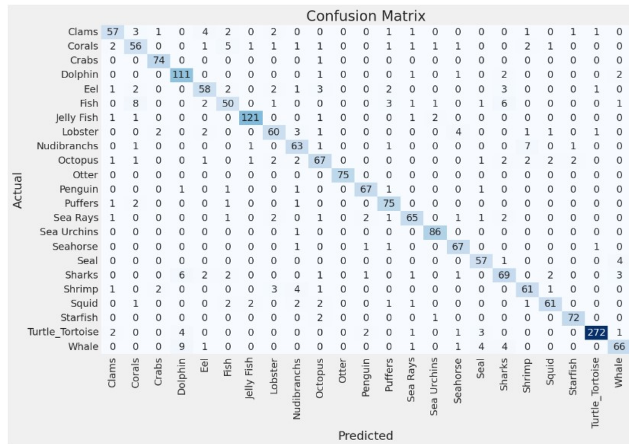

Fig. 3: Confusion Matrix

Fig. 3 is based on the evaluation where the values of accuracy, precision, recall, and F1-score have been standardized in the form of a confusion matrix.

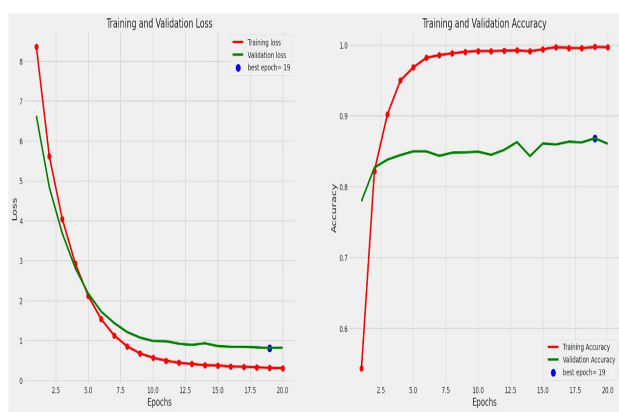

Fig. 4: Accuracy

Fig. 4 The model is based on a measure of prediction accuracy. It is represented as the ratio of properly categorized examples to the total number of instances used in the testing set. It gives an overall summary of the performance of the model.

D. Classification Report

The classification report for the CNN-based model used to classify marine animals is highly promising. The model

TABLE II: Classification Report

Animals	Precision	Recall	F1-score
Clams	85.07%	77.03%	80.85%
Dolphin	84.73%	94.07%	89.16%
Eel	81.69%	77.33%	79.45%
Jelly Fish	96.03%	95.28%	95.65%
Octopus	80.72%	79.76%	80.24%
Penguin	91.78%	93.06%	92.41%
Seahorse	87.01%	94.37%	90.54%
Sharks	77.53%	78.41%	77.97%
Shrimp	81.33%	83.56%	82.43%
Whale	85.71%	76.74%	80.98%
Accuracy			87.99%
Macro Avg	86.61%	86.87%	86.66%
Weighted Avg	88.01%	87.99%	87.92%

demonstrates remarkable accuracy in identifying and categorizing different species of marine animals. The model achieves excellent performance with a methodical approach encompassing data collection, preprocessing, architecture design, training, tuning, and assessment. The CNN-based model's success underscores its potential to contribute significantly to marine biology research and conservation efforts.
The following Table 2 encapsulates the outstanding outcomes of our CNN-based model for marine animal classification. It reflects the model's remarkable accuracy in distinguishing and classifying diverse marine species, reaffirming its potential as a valuable asset in marine biology research.

E. Prediction

A truth table is a table that is used to organize the many truth values that may be associated with a logical assertion. A truth table is also known as a truth matrix. True may take on many distinct meanings, including true, false, one, or zero. These are only some of the possible values. Even though it does not happen very often, values may sometimes use a different binary scheme, such as on/off or open/closed, for example. This is something that does not happen very frequently. However, this kind of thing only happens once in a blue moon. In order to determine the solutions to such mathematical problems, one option is to consult a truth table.

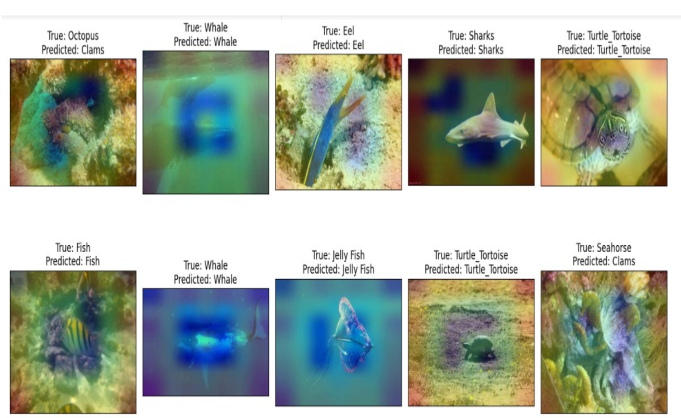

Fig. 5: Prediction

TABLE III: PERFORMANCE ANALYSIS COMPARISON

Reference	Focused Method	Accuracy
Previously	EfficientNet B7+ MobileNet V3	82.21%
Proposed	EfficientNet B0+EfficientNet B3+EfficientNet B5	87.99%

In Fig. 5, the results of this model have been shown in the diagram in the form of expression variables, and the rows in the design have been designed to represent the many possible truth values. Both of these aspects are included in the design. In addition, there is a column that provides a breakdown of the individual value combinations and the results obtained by combining those values. This image is given below.

F. Final Result and Discussion

The results of our works are tabulated in Table 3, which shows a visualization of accuracy. As seen here, the accuracy of our proposed model seems to be 87.99%, which is good enough. This seems quite better in comparison to previously applied models, and this accuracy is obtained in a situation involving the classification of marine animals. Our approach keeps the accuracy high enough, which is a remarkable achievement. Presented in Fig. 6 is a visual representation of our proposed model, demonstrating an impressive advancement over prior methods for classifying marine animals. This advance greatly aids marine research, conservation, and our grasp of underwater ecosystems and species diversity.

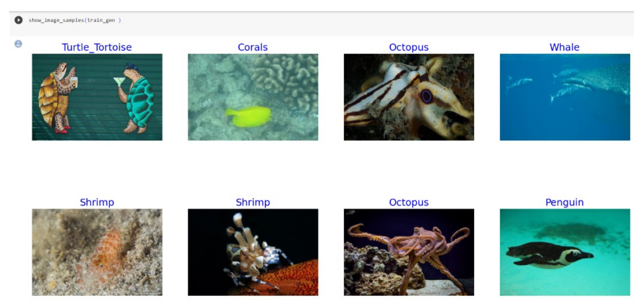

Fig. 6: Different types of Marine Animal

This model is satisfactory for our system. The way this system stays consistent even with high accuracy is a remarkable achievement.

V. Conclusion

Deep learning and convolutional neural networks (CNNs), which are a kind of artificial neural network, were investigated to determine whether they are capable of correctly classifying marine species. This investigation was conducted as a component of a thesis. It has been demonstrated by in-depth testing. Several studies indicate that CNNs, in particular, are extremely successful. in accurately classifying aquatic species based on the visual characteristics they have. This conclusion was reached. Large datasets, pre-trained models, and cutting-edge architectures such as EfficientNet B0, EfficientNet B3, and EfficientNet B5 were utilized in concert with one another to obtain outstanding accuracy rates in the classification process.EfficientNet B0, EfficientNet B3, and EfficientNet B5 were used as examples to achieve this. Methods of data enhancement, such as rotating and inverting photographs, were used in order to make the models more robust and relevant to a larger variety of scenarios. The findings of this research show that deep learning approaches have the potential to be useful for a variety of tasks involving the categorization of pictures, including the possibility of advancing research on marine life. In addition, these results provide evidence that deep learning approaches have the potential to become more advanced.

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