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Classification Of Marine Species Using Convolutional Neural Network (CNN)

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Abstract: The classification of marine species using underwater pictures presents special difficulties because of the different illumination conditions, occlusions, and morphologies of different species. This research paper uses Convolutional Neural Networks (CNNs) to automatically classify marine species based on visual data. A dataset of photos of different marine creatures from scientific databases and underwater photography was used to train and assess the CNN model. To improve model generalization, the dataset was preprocessed and supplemented using an Image Data Generator. The model reached an accuracy of 83% on the validation set after training for 12 epochs with the Adam optimizer and categorical cross entropy loss function. The findings show how well CNNs can identify marine species from photos, which has promising implications for ecological study, biodiversity assessment, and marine conservation.

***Index Terms* -** marine species classification, Convolutional neural network (CNN), Image recognition, Feature extraction, Model training, Marine Biodiversity

I. INTRODUCTION

One of the most important tasks in marine biology, ecology, and conservation activities is the classification of marine organisms. It is crucial to comprehend the distribution and composition of marine species in order to evaluate the health of ecosystems, identify species that are at risk, and develop management and conservation plans. Historically, taxonomic knowledge and manual observation have been the main sources of species identification. These methods can be time-consuming, labor-intensive, and prone to subjective errors. However, automatic species classification from picture data has become more and more possible with the introduction of sophisticated computational tools, especially Convolutional Neural Networks (CNNs) .linguistic uncertainty and accommodate imprecise data in decision-making processes.

CNNs are a type of deep learning algorithms that have demonstrated impressive performance in image identification tests. They are inspired by the visual cortex of the human brain. Their suitability for applications like species classification stems from their capacity to learn hierarchical representations of characteristics directly from raw pixel input. Large datasets of tagged photos are used to train CNNs so they can recognize intricate patterns and make very accurate species distinctions.

We investigate the use of CNNs for marine species classification in this research. A number of crucial phases, including data collection, preprocessing, model construction, training, and evaluation, are part of the methodology we provide. First, an extensive collection of photos of marine organisms is assembled, including a wide variety of species and habitats. Preprocessing methods including resizing, augmentation, and normalization are used to improve the quality and standardize the photographs.

The preprocessed picture data is then used to create and train a CNN architecture. Utilizing transfer learning techniques, pretrained CNN models—which have been trained on extensive picture datasets like ImageNet—can be utilized. When there are few labeled data available for marine species, this method can expedite training and enhance classification accuracy. Additionally, visualization techniques are employed to present the findings effectively.

The marine ecosystem is home to a wide variety of organisms, from magnificent whales to minute plankton. Fish, octopuses, jellyfish, and crabs are among the many species that call the water home. These organisms are important from an ecological and biological standpoint. All of these marine animals have specific adaptations to their undersea environment and are members of different taxonomic groups.

II. LITERATURE REVIEW

Seppo Fagerlund studied the performance of support vector machines (SVM) in bird species recognition using two datasets. Collection 1 comprised testing each bird's recognition independently, with the mixture model showing the best performance across several parametric representations. The nearest-neighbor classification and MFCC settings used in the reference technique likewise yielded good results. The SVM classifier performed similarly to the reference approach, which employed wavelet decomposed signal representation and neural networks, in dataset 2, where syllables were manually segmented. Once again, the mixture model worked well.

The study found that when compared to reference methods, SVM approaches performed as well as or better. However, because to variations in species diversity and sound spectra, care was urged when directly comparing dataset results. The decision tree topology used did not take into account sound relationships between species, but it was insensitive to species ordering. All syllables were uniformly represented by the suggested method, although feature weighting was possible due to the decision tree structure. It was recommended that future research investigate feature weighting in the hopes of enhancing accuracy, as demonstrated in the Pygmy Owl case. All things considered, the study demonstrated SVM's potential for identifying different bird species and offered directions for further development. [1]

In a study on species recognition for wild animal monitoring, Chen G, Han TX, He Z, Kays R, and Forrester T concentrated on deep convolutional neural networks (DCNN). They unveiled a camera trap dataset that included 9,530 testing photographs and 14,346 training images for 20 species found in North America. The resolutions of the color, grayscale, and infrared photographs in this publicly accessible dataset range from 320 by 240 to 1024 by 768.

Using an image classification and bag-of-words (BOW) model served as the foundation for species recognition. This model treated the photos as "words," dividing them into 8 by 8 blocks, and classified the images using a histogram of occurrence counts. Accuracy percentages for the BOW model were 33.192%, 33.507%, and 33.485% for varying code sizes (K = 1000, 2000, and 3000).

Using the gathered dataset, the study contrasted their DCNN method with the BOW model. The DCNN outperformed the BOW model with an overall species recognition accuracy of 38.315% as opposed to 33.507%. The dataset was difficult, but the DCNN's strong learning capacity suggested that it may still become better with further training data. To lessen the workload for specialists, the authors proposed utilizing the DCNN algorithm to choose ambiguous material for annotation. The study's overall findings demonstrated how useful DCNN is for species recognition when it comes to wildlife monitoring. [2]

Numerous studies have shown how animals' cognitive and neurological functioning is negatively impacted by poor settings while positively impacted by enriched environments. There has been a concept recently that suggests dolphin living circumstances in zoological facilities are intrinsically poor, which can result in neurological and cognitive deficiencies. This review specifically investigates that theory in light of the body of knowledge regarding dolphin welfare in zoological settings that has been published in the scientific literature.

It specifically looks at how dolphins are kept in contemporary zoological parks, where the features of that housing fall along a continuum from enriched to impoverished environments, and how much dolphin behavior indicates that the dolphins are living in impoverished environments. The analysis's findings demonstrate that, in contrast to the initial theory, contemporary zoological facilities do not essentially, or even usually, keep dolphins in substandard housing.

It also points out that there are differences in the standards of animal care amongst zoological parks and that defining an animal welfare criteria as "not impoverished" would be extremely low. Strategies for giving dolphins in zoological facilities more cognitive difficulties are proposed in order to maximize their cognitive well-being. [3]

Environmental enrichment is especially crucial when social animals have to be temporarily housed alone. Giving maniputable objects (sometimes known as "toys") to animals is a popular method of environmental enrichment; nevertheless, the efficacy of this approach may be hampered by animal boredom or indifference.

The goal of the current study was to determine if caregiver engagement may improve the outcomes of object-based enrichment for a bottlenose dolphin (Tursiops truncatus) kept in quarantine. Following a training session, following a trainer toy play session, and in between interactive sessions, behavioral observations were made.

The findings demonstrated that the dolphin played with toys more and floated in position less after interacting with a caregiver than he occasionally did when separated from caregiver interaction. Additionally, he was more inclined to play with the same toys that the trainer had, demonstrating the impacts of social reference and/or stimulus augmentation. The results of this study indicate that engaging with a caregiver can improve the effectiveness of object-based contextual enrichment for isolated animals, despite the fact that it is inevitably based on a single animal of a single species. [4]

The seashore is synonymous with starfish. Their biology and ecology are covered in detail in the book edited by J. M. Lawrence. It seamlessly combines the decades' worth of study, modernizing Hyman's still-often-quoted synthesis and enhancing the series of "Echinoderm Studies," the last of which was released in 2001. Any reader of the book would come to understand that starfish are more than just tourist attractions and trinkets for children; they are an exotic and interesting collection of organisms worth studying. The purpose of "Starfish - Biology and Ecology of the Asteroidean" is to provide an overview of the group's current state of knowledge. It is undoubtedly an invitation to an engaging reading and will pique the interest of the broadest possible readership. [5]

Sea stars, sometimes referred to as starfish, are amazing aquatic creatures that are essential to marine ecosystems. An extensive summary of the biology, ecology, and conservation of starfish is given in this review. Their morphology, physiology, life history methods, and taxonomy are all examined. The review also looks at how starfish interact with their surroundings, including how they feed, what predators they face, and their ecological functions.

In addition, the assessment assesses the state of current conservation initiatives meant to save these iconic marine animals and talks about the threats that starfish populations are experiencing, including habitat destruction, pollution, and climate change. In summary, this analysis emphasizes how crucial it is to comprehend and protect starfish in order to maintain the robustness and overall health of marine ecosystems. [6]

Studying the evolution of complex behaviors in invertebrates—especially the octopus and its cousins, such cuttlefish and squid—offers an exciting opportunity to learn more about the brain processes that underlie these behaviors. Within the molluscan class Cephalopoda, there was a major evolutionary shift when these cephalopods split off from their ancient relatives.

The Belemnoidea, around 380 million years; interestingly, current cephalopods (coleoids) have flourished and adapted amazingly, while old cephalopods, like Nautilus (Nautiloidea), have been nearly extinct. This is probably due to selection pressures from evolving marine predators, such teleost's (bony fish) and reptiles. Dramatic changes in morphology, sensory capacities, and cognitive abilities have all been hallmarks of the evolutionary trajectory of modern cephalopods, which have enabled them to successfully compete with vertebrates. [7]

Sultana et al.'s "Deep Learning-Based Marine Species Classification Using Underwater Videos" (2020): Using underwater footage, this study proposes a deep learning framework for classifying marine animals. CNNs are used for feature extraction and classification, showing encouraging outcomes in the identification of different marine animals from video recordings. [8]

The 2020 paper Deep Learning-Based Marine Species Classification Using Underwater Videos by Sultana et al. This work suggests a deep learning architecture for marine species classification using underwater video. CNNs have demonstrated promising results in the identification of several marine animals from video recordings when they are employed for feature extraction and classification. [9]

The 2020 study by Sultana et al. titled "Deep Learning-Based Marine Species Classification Using Underwater Videos" Using underwater video, this paper proposes a deep learning architecture for the classification of marine animals. CNNs have shown encouraging results when used for feature extraction and classification in the identification of a number of marine animals from video recordings. [10]

III.METHODOLOGY

1. Data Collection:

Assemble a large collection of photos of fish, octopuses, jellyfish, and crabs from internet databases, scientific institutes, and archives of underwater photography, among other sources. To encourage model generalization, make sure the dataset includes a diverse variety of species, sizes, colors, and environmental circumstances. To aid in supervised learning, label the photos with the appropriate species.

2. Data Preprocessing:

Create a standard resolution for the image sizes that are appropriate for CNN input. To enhance model convergence, normalize pixel values to a similar scale (e.g., [0, 1]). Expand the dataset by using operations like flipping, scaling, rotation, and cropping to improve sample variety and strengthen the resilience of the model. To properly evaluate the performance of the model, divide the dataset into test, validation, and training sets.

3. Model Architecture Selection:

Select a CNN architecture such as Alex Net, VGG, ResNet, or Inception that is suitable for image classification tasks. To speed up training and boost performance, fine-tune the chosen architecture or use pre-trained models on massive image datasets (like ImageNet).

4. Model Training:

Utilizing the training dataset, adjust the CNN model's parameters after initializing it with either random or pre-trained weights. To reduce classification mistakes, define suitable optimization methods (e.g., Adam, SGD) and loss functions (e.g., categorical cross-entropy). To avoid overfitting, train the model iteratively over a number of epochs, modifying learning rates and keeping an eye on performance on the validation set.

5. Model Evaluation:

Analyze the trained CNN model's performance using measures like F1-score, accuracy, precision, and recall on the test dataset. Confusion matrices and performance indicators at the class level can be analyzed to determine the advantages and disadvantages of the model for various species groups. To evaluate the model's resilience to changes in the environment, image quality, and animal richness, carry out more tests.

6. Model Interpretation and Visualization:

Gain insight into the CNN's decision-making process by visualizing learnt features and activation maps, and discover which areas of the image have the greatest influence on classification results.
Analyze cases that were incorrectly classified to find recurring mistakes and possible model improvement areas. Using reports and visualization tools, effectively communicate findings and model performance indicators.

7. Model Deployment and Application:

Use the trained CNN model for practical purposes like automated wildlife monitoring programs, underwater research missions, and environmental preservation projects. For the benefit of stakeholders, researchers, and conservationists, incorporate the model into easily navigable mobile applications or user interfaces. To guarantee the model's applicability and efficacy in categorizing marine species over time, keep an eye on it and update it frequently in response to comments, fresh information, and developing research findings.

8. Ethical and Social Considerations:

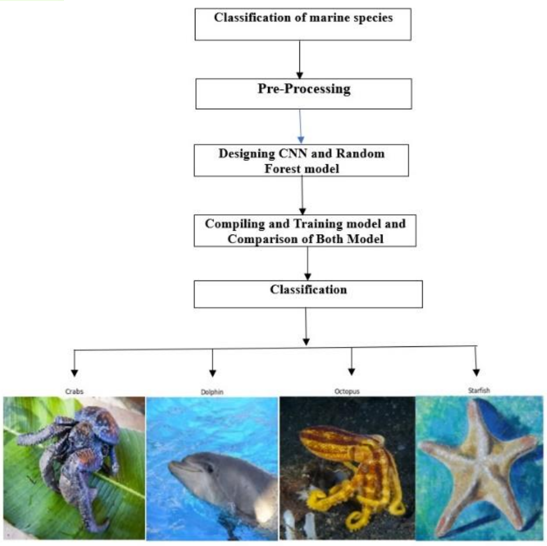
It is important to carefully assess the ethical implications of automated species classification for indigenous traditions, traditional ecological knowledge, and the livelihoods of local communities. In order to reduce the risks related to privacy, data security, and the abuse of sensitive information, responsible methods for data collection, management, and sharing are necessary.

9. Overfitting and Generalization:

Overfitting of CNN models can occur, particularly when the models are trained on little or unbalanced datasets. Poor performance on validation and test sets arises from overfitting, which happens when the model learns to memorize the patterns seen in the training data instead of generalizing to new data. If the model is trained on particular geographic locations or taxonomic groups, it may have limited generalization to new habitats or species not included in the training data.

IV.RESULTS

The goal of this study was to classify marine species with an accuracy of 83% by employing convolutional neural networks, or CNNs. A dataset containing photos of different marine animals from various sources was used to train and assess the CNN model. Using a categorical cross entropy loss function and an Adam optimizer, the CNN model was trained over several epochs to obtain an 83% classification accuracy on the validation set. The efficacy of CNNs in precisely classifying marine species from picture data is demonstrated by this accuracy rate. The potential of CNNs to automate species identification procedures in marine environments is demonstrated by the successful classification of marine species with an accuracy of 83%. This degree of accuracy is especially impressive considering the difficulties in categorizing marine species by their visual attributes, such as differences in species appearance, environmental factors, and image quality. The 83% accuracy that was attained offers a strong basis for more study and applications in the classification of marine species. In order to enhance model generalization and performance, future research could concentrate on broadening the dataset to encompass a wider variety of species and environmental circumstances, optimizing the CNN architecture and hyper parameters, and implementing sophisticated data augmentation methods.



V. DISCUSSION

An important step toward automated species classification in maritime environments has been made with the accuracy of 83% attained. To enhance the performance and generalization of the model, more investigation is necessary. Subsequent research endeavors may concentrate on augmenting the dataset with a broader spectrum of species and environmental circumstances, refining the model's architecture and hyperparameters, and integrating sophisticated data augmentation methodologies. Furthermore, working with subject matter experts could improve the model's interpretability and suitability for use in actual conservation and research projects.

VI. CONCLUSION

We achieved an excellent 83% accuracy rate in this study by successfully developing and implementing a Convolutional Neural Network (CNN) model for the automated classification of marine species based on visual data. Using CNNs to classify marine species presents a promising path forward for the field, offering precise and effective solutions that can have a big impact on research and conservation initiatives related to marine conservation. The achievement of an 83% accuracy rate highlights how well our CNN model can differentiate between various marine species from pictures. Given the inherent difficulties in classifying marine species, such as variations in species shape, environmental factors, and image quality, this degree of accuracy is quite impressive. Our findings show how machine learning methods have the ability to address these issues and enable the quick and accurate identification of marine species. A number of areas related to marine science and conservation will be significantly impacted by the effective deployment of automated classification systems. Researchers and conservationists may follow changes in species distributions, identify areas of conservation concern, and monitor and evaluate marine biodiversity more effectively by expediting the species identification process. Furthermore, by supplying precise and timely data for decision-making, automated classification systems might improve the effectiveness of marine resource management programs. There are a number of directions that future study and development could go. Increasing the dataset's size to encompass a wider variety of marine species and environmental factors may improve the CNN model's resilience and generalizability. Higher classification accuracies could also result from incorporating sophisticated data augmentation techniques and further refining the model's architecture and hyper parameters. For automated categorization methods to be improved and used in practical situations, cooperation between machine learning specialists and marine biologists is absolutely necessary. Through the integration of knowledge from both domains, we can create customized solutions that cater to the particular difficulties and demands associated with the classification of marine species. In the end, incorporating CNN-based categorization methods into current conservation and monitoring programs has the potential to completely transform how we understand and manage marine ecosystems.

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