Comparative Analysis of Deep Learning Models for Marine Species Classification: CNN, ResNet50, and SE-CNN Approaches

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Abstract — The classification of marine species is essential for biodiversity conservation and ecological monitoring. In this study, we compare three deep learning models—Standard Convolutional Neural Network (CNN), Transfer Learning using ResNet50, and Squeeze-and-Excitation CNN (SE-CNN)—to evaluate their effectiveness in identifying marine species. A dataset consisting of 16,616 images of six marine species was used for training and testing. The models were assessed based on accuracy, computational efficiency, and class-wise performance analysis. Experimental results indicate that SE-CNN outperforms the traditional CNN model, while ResNet50 achieves high accuracy with minimal training effort. Our findings provide insights into selecting optimal models for marine species classification and contribute to AI-driven ecological monitoring solutions.

Keywords: Convolutional Neural Network (CNN), Squeeze-and-Excitation CNN (SE-CNN), Deep Learning Models, ResNet50

I. Introduction

The ocean is home to a vast and diverse range of marine life, playing a crucial role in maintaining global ecological balance. However, human activities such as overfishing, pollution, and climate change threaten marine biodiversity. Effective monitoring and classification of marine species are vital for conservation efforts. Traditional species identification methods are time-consuming and require expert knowledge. Recent advancements in deep learning offer automated solutions for species classification with high accuracy.

This study explores three deep learning models—Standard CNN, ResNet50-based Transfer Learning, and SE-CNN—to determine the most effective architecture for marine species classification. By evaluating accuracy, computational performance, and misclassification trends, we aim to contribute to the development of efficient AI-driven marine classification systems that can aid in real-time monitoring and ecological assessments.

II. Literature survey

Over the past few years, deep learning has gained prominence in ecological and biodiversity research. Several studies have explored the effectiveness of machine learning and deep learning in species classification.

Bang et al. (2023) reviewed the impact of deep learning on marine species classification, demonstrating how CNN-based models have surpassed traditional feature-engineered approaches. Their findings highlighted the potential of data augmentation and transfer learning in enhancing classification accuracy.

Khan et al. (2024) examined the use of deep learning in ecological monitoring and proposed a hybrid approach combining CNNs with attention mechanisms. Their research emphasized that advanced deep learning techniques can significantly improve species identification accuracy, particularly in underwater environments where image quality varies.

Moro-Velázquez et al. (2022) investigated ResNet-based transfer learning approaches and found that pre-trained models improve classification performance, even with limited labeled data. The study demonstrated that fine-tuning ResNet50 with domain-specific data yielded substantial improvements in marine species classification.

Hoque et al. (2024) introduced a novel Squeeze-and-Excitation CNN (SE-CNN) model for marine biodiversity conservation, proving that recalibrating feature maps using SE blocks can significantly enhance model performance. Their study reinforced the importance of incorporating feature refinement techniques in deep learning-based classification tasks.

These studies establish a foundation for our research by highlighting the advantages of deep learning models, transfer learning, and feature recalibration techniques in marine species classification.

III. Methodology

A. Preprocessing Techniques

Preprocessing plays a vital role in enhancing model performance. The following preprocessing techniques were applied to the dataset:

- Image Rescaling: Normalization of pixel values to the [0,1] range to ensure consistency.
- Data Augmentation: Rotation, zooming, flipping, and translation to increase dataset variability and reduce overfitting.
- Class Balancing: Ensuring a balanced representation of different species in training data to prevent biased learning.

B. Dataset

The dataset consists of 16,616 images (8,224 for training and 8,392 for testing) spanning six marine species. It was divided into training, validation, and testing subsets to optimize model performance. The dataset was collected from multiple marine biodiversity sources and manually labeled by experts to ensure accuracy.

C. Model Development

- Standard CNN: A sequential model consisting of convolutional layers, batch normalization, max pooling, and fully connected layers for feature extraction and classification.

– ResNet50 (Transfer Learning): A pre-trained ResNet50 model with additional dense layers fine-tuned for marine species classification.
– SE-CNN: A CNN integrated with Squeeze-and-Excitation (SE) blocks to enhance feature extraction by recalibrating feature maps and improving classification accuracy.

D. *Model Training and Testing*

1) Training Configuration:

- Optimizer: Adam
- Loss Function: Categorical Crossentropy
- Batch Size: 32
- Epochs: 10 (ResNet50), 15 (SE-CNN), 20 (CNN)
- Framework: TensorFlow & Keras

2) Evaluation Metrics:

- Accuracy
- Loss
- Training Time
- Confusion Matrix for class-wise performance analysis

IV. RESULTS AND OBSERVATIONS

The models were evaluated based on test accuracy and computational efficiency, with results summarized in the table below:

Model	Test Accuracy (%)	Training Time
Standard CNN	85.2	Moderate
ResNet50	92.5	Low
SE-CNN	94.1	High

A. *Visualization of Results*

To further analyze model performance, the following visualizations were generated:

– Accuracy and Loss Curves: Tracking model convergence and performance over epochs.
– Confusion Matrix: Examining class-wise performance and identifying misclassification trends.
– Feature Activation Maps: Understanding model attention and decision-making patterns.

Among the three models, SE-CNN achieved the highest accuracy, benefiting from improved feature extraction using SE blocks. ResNet50 offered a balance between accuracy and training efficiency, making it a viable option for real-world applications. While the standard CNN performed well, it was slightly less effective than the other two models, highlighting the advantages of advanced architectures.

V. CONCLUSION

This study highlights the potential of deep learning for marine species classification. The SE-CNN model demonstrated superior accuracy, while ResNet50 provided an optimal trade-off between accuracy and training time. Our results suggest that incorporating attention mechanisms like SE blocks can significantly enhance CNN-based classification models. Future research can explore hybrid models combining CNNs with attention-based architectures or applying explainable AI techniques to better understand model decision-making processes. Additionally, expanding the dataset with more marine species and integrating real-time classification into underwater monitoring systems can further enhance AI applications in marine biodiversity conservation.

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