XCEPFOREST: A HYBRID DEEP LEARNING AND MACHINE LEARNING APPROACH FOR ENDANGERED AQUATIC SPECIES CLASSIFICATION

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Abstract
From the appearance of Homo sapiens until now, innumerable species have gone extinct, and many marine organisms are now on the verge of extinction due to human activity and changing environmental conditions. In this study, we proposed a hybrid model for endangered aquatic species classification based on deep learning and machine learning. We use the Xception Pre Trained Model for high-level image feature extraction, followed by Random Forest classification and termed it "XcepForest". We utilized the data downloaded from iNaturalist which was annotated with video frames extracted from the trusted accounts, and performed bilateral filtering and adaptive gamma correction for better image quality before feeding into the model. Across an 80-20 train-test split, XcepForest achieved 92.73% accuracy on the training set and 92.45% accuracy on the test set, successfully annotating species including the green sea turtle, whale shark, and blanket octopus. Overall, the majority of existing research has focused on the classification of fish and other marine mammals, and often requires high computational power and does not aim for the monitoring of endangered species. Thus combining deep feature extraction with a machine learning classifier, provides an efficient and scalable solution to the conservation of marine biodiversity.

INTRODUCTION

The marine environment, which comprises about three-fourths of Earth, supports thousands of species of plants and animals, most of which remain unknown [1]. The biodiversity of the ocean spans from microscopic (not visible to the naked eye) plankton to giant blue whales, making it one of the most diverse ecosystems on Earth. But the diversity of marine life is under threat and many species, including the green sea turtle, the whale shark and the blanket octopus, are experiencing rapid population declines. Direct human activities like illegal fishing affect these species with immediate effects, while climate change compounds the problem through widespread and cascading impact on marine habitat.

Traditional monitoring and classification of endangered marine species has significant challenges, including lack of scalability, inefficiency and inaccuracy [2], that limit effective conservation of endangered marine species. To address these challenges, this work proposes an AI framework that uses deep learning for data abstraction and machine learning for classification. Leveraging the strengths of both Xception, which is a deep convolutional neural network with the capability of higher accuracy on species classification tasks, and Random Forest, which is a strong and interpretable classifier, we aim to achieve better classification accuracy, higher efficiency, and lower computational burden.

In order to classify marine species, we used a hybrid of deep learning and machine learning. Taking advantage of complex environment and a definite pattern identification ability in identifying image cross-targets, our model adopts the pre-trained Xception convolutional neural network [3] to extract features before the final prediction. Finally, Random Forest is used to classify the extracted features, being interpretable and computationally efficient. This marriage of the two techniques, coined as XcepForest, allows classification to be conducted more accurately, and with lower computational demands. We assembled a heterogeneous dataset of images from iNaturalist and augmented video frame [4] to train and test the model. The preprocessing steps included the use of bilateral filter to reduce noise and enhance lighting using adaptive gamma correction, leading to high-quality focus input for feature extraction. Moreover, a number of data augmentation techniques rotation, flipping and zooming were also used to improve variability and improve the generalization of the model.

In this work we have presented the new hybrid approach, XcepForest, leading to accurate and efficient classification of endangered marine species. Training on three class labels, our model inherits Xception's power of extracting features, and Random Forest's ability to interpret them, creating a solution that is scalable and targetable to enhance marine conservation effort. This work is important for the protection of endangered species and helps establish balance within marine biomes.

Whale Shark

The Whale Shark is the first entry on our endangered species list due to unique Biology / ecological roles They provide our first glimpse into an ancient and complex immune system and the ability to produce substances that will fight disease. Their huge size and the inevitable risk of cancer made them a tempting source of potentially useful information in research in most cases . The Whale shark is also an ocean natural filter [5], it has hundreds of small teeth with filter pads with function of capturing food particles while passing the water. It is also analyzed as a theory in the development of simulated models associated to ecological applications [6]. Each gene in the whale shark's genome contains a story of survival and adaptation, which makes them a living repository of Earth's biological history .

Blanket Octopus

The Blanket Octopus is also perfect for research as it is in the endangered species list as well as its general level of intelligence and adaptive abilities [7]. This Octopus displays complex problem-solving abilities and advanced camouflage [8] — which to this day play a crucial role in its survival. The chemical sensitivity of their arms, which serve as their biggest hands, are important for maneuvering through the water and avoiding predators. They also interestingly can change their colour and release ink as an armament [9]. Therefore, working with them will provide more insight into cephalopod intelligence, neurobiology, and evolutionary biology, corresponding research on them will enlighten each of these fields of study even more.

Green Sea Turtle

One endangered species that serves as a critical bioindicator is the green sea turtle, which provides invaluable information on the overall health of the marine ecosystems in which it exists . As they travel the oceans, they collect evidence of pollution and pathogens (disease-causing microorganisms), showing how human actions affect ecosystems of these large bodies of water. Their physiology and behavior can thus be used by scientists to assess the levels of pollution, disease prevalence, and overall health of the ocean . This natural variation makes them ideal indicators of environmental changes and for exploring methods to protect marine organisms from adverse effects of human pollution and climate change [10]. That's why green sea turtle is an important species for environmental monitoring and conservation efforts [11].

Literature Review

Deep learning and computer vision are applied to species recognition and conservation across multiple applications in the aquatic environment, including (but not limited to) fish detection, classification, and health monitoring; automated fish counting; coral reef monitoring; and invasive species identification However, there is limited work on endangered marine species (e.g., green turtles, blanket octopuses, and whale sharks). This disparity emphasizes the need for more effective techniques to classify and monitor these vulnerable organisms that are key to the stability of marine biodiversity and functioning of marine ecosystems.

Deep learning-based methodology has been demonstrated to enhance characteristics of aquatic species recognition, primarily for fish, with considerable discrepancy in classification accuracy. For instance, deep learning based research for underwater fish species classification that utilized Convolutional Neural Network (CNN) which gives an accuracy of 96.29% [12]. Like Fernandez Garcia [13], designed a deep neural network for multi-species fish detection with multiple acoustic cameras; their approach demonstrates the potential for AI-driven solutions in aquatic environments. By leveraging on these advantages, we propose a hybrid model XcepForest able to capture relevant features from the Xception network and retain the interpretability of a Random Forest classifier. XcepForest was able to achieve a training accuracy of 92.73% and a testing accuracy of 92.45%. Though modestly lower than some of the published accuracies for fish classification, these results are impressive in consideration of further obstacles to recognizing the endangered species in our dataset (green turtles, blanket octopuses and whale sharks), as they are data poor and contain greater visual variability.

One more notable contribution to the field of species classification in the underwater setting was the work and trained a deep CNN to classify a set of seagrass species from images underwater, resulted in 92.4% accuracy[14]. In this study, a semi-automated labeling method was developed to address the high volume of images that are typically reviewed in the context of underwater surveys, thereby significantly alleviating the need for manual annotation of imagery. They open-sourced their dataset, code and pre-trained model, enabling the wider researcher's community to reproduce and build upon their experiments. Although this study showed the promising ability of deep learning for species classification beyond fish, it is specifically using seagrass dataset and does not concern endangered marine species. In comparison, our hybrid method XcepForest obtained 92.73% accuracy in training and 92.45% in testing, providing a scalable and efficient means of identifying at risk species, such as green turtles, blanket octopuses, and whale sharks.

Specifically, due to their resource-efficient architecture and mobile and embedded vision applications, MobileNetV2 has become another key component in the marine species classification pipeline. This research [15], achieved an impressive accuracy of 99.83% by optimizing MobileNetV2 with a specifically curated dataset and extensive augmentation techniques. Although these studies highlight the successes of MobileNetV2 for identifying non-endangered species, our work investigates the opposite direction. We employ Xception for feature extraction and Random Forest for classification, obtaining a training accuracy of 92.73% and a testing accuracy of 92.45%. We introduce a hybrid approach designed to identify endangered marine species including green turtles, blanket octopuses and whale sharks, which is scalable and practical for marine conservation.

To address the limitations of traditional CNN-based algorithms in complex underwater environments, Zhao et al. proposed Composite FishNet framework [16]. This framework can be applied to fish detection by designing a new composite backbone network (CBresnet) and enhanced path aggregation network (EPANet), which marked a significant improvement in average precision and recall, which demonstrate its applicability for fish detection and identification in challenging conditions.

Tha Lavanya [17], utilized three models which include VGG16, MobileNetV2 and ResNet50 on Fish4Knowlege dataset but got only the accuracy of 94.96% for MobileNetV2 as the highest and 91.61% for VGG16, while the RestNet50 was only able to achieve the accuracy of 85.71%.

Underwater object detection can be extremely challenging due to the low visibility underwater as well as environmental noise and in some cases pollution from human activity. The Brackish-Dataset has recently been used to evaluate models like YOLOv5, YOLOv8, EfficientDet, and Detectron2 [18]. These results were achieved on EFFICIENT-Det net, which outperforms others when resided with modified of the

BiSkFPN mechanism. The idea of adversarial learning is also
used to gain better performance, achieving state-of-the-art mAP of 98.63% for EfficientDet.
To summaries, although present research is mainly concerned with the taxonomy of fish and other marine mammals, it often demands significant computational resources and lacks targeted applicability to endangered species. To address this limitation, we propose XcepForest, a hybrid framework that integrates Xception as a feature extractor and Random Forest as a classifier. In particular, our method is tailored for makeshift use on endangered species (e.g., green turtles, blanket octopus, and whale sharks). The XcepForest outperforms expectation with a training accuracy of 92.73% and a testing accuracy of 92.45% making this a valid and robust solution for the classification of endangered species. Not only does this framework allow rapid species identification, but it also serves to facilitate future conservation efforts and sustain marine environments.

Table 1: Summary of Literature Review

Study	Model	Accuracy	Dataset
Rathi et al. (2018)	CNNN	96.29%	Custom Dataset of underwater fish
Fernandez Garcia et al. (2021)	YOLOv3	~80% detection	Acoustic images from DIDSON and ARIS cameras, including species like Atlantic salmon and European eels
Lavanya, G et al. (2024)	VGG16, MobileNetV2, ResNet50	91.61% 94.96%, 85.71%	Fish4Knowledge dataset
Ranie, S et al. (2020	Deep CNN	92.4%	Custom dataset of seagrass images collected during underwater surveys.
Dey, l at el. (2023)	MobileNetV2	99.83%	Dataset created through specific guidelines and augmentation techniques for marine species images.
Jain,S. at el. 2023	YOLOv5, YOLOv8, EfficientDet, and Detectron2	98.63% mAP	Brackish-Dataset

Dataset

A- Dataset Collection

1) **iNaturalist Image Collection:** Our primary data source was iNaturalist, a citizen science platform where nature lovers and researchers post reports of life found in the wild . From iNaturalist, we collected a diverse set of images — including 2,900 of the Green Turtle, 150 of the Blanket Octopus, and 2,800 of the Whale Shark. This sampling PowerPoint demonstrates the biological variation within these species among environmental environments and conditions to cut down on data set size and increase data richness. The opportunistic collecting that happens on iNaturalist ensures variability and context that add to understanding of habitat features.

2) **Video Frame Extraction:** We also obtained more diverse data by extracting frames from (long) video sources such as National Geographic. This produced 642 additional images showing the Green Turtle, 540 of the Blanket Octopus, and 750 of the Whale Shark. Video frames give more than just different angles of a static scene — they capture interesting dynamics and more environmental context.

3) **Dataset Composition:** The data used for training our AI model consisted of an amalgamation of images collected from iNaturalist in addition to video frames. By collecting images from multiple sources, we guarantee that a wide distribution of each species is represented to enable accurate classification and increase the robustness and generalization of our model. The variability in all of the environmental conditions, perspectives, and angles to the data provided to the model helps classify endangered marine species accurately and reliably. The distribution of dataset can be visualized in Figure 1.

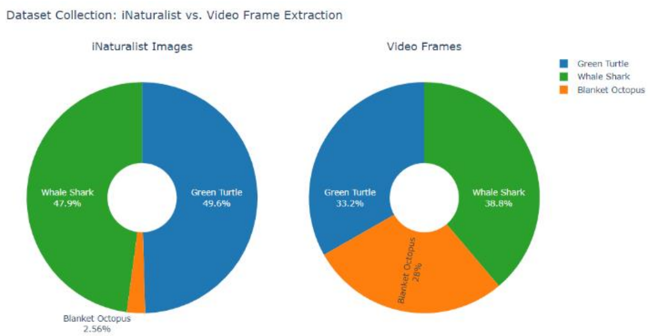

Figure 1: Dataset sources for Green Turtle, Blanket Octopus, and Whale Shark. Left: iNaturalist images. Right: video frames

B- Preprocessing of Collected Data

Data was collected by using various search engines for images, specifically focusing on ground and aerial photographs, and dank memes all under the category of not current events, while those collected were sufficient, they would need to go through several preprocessing steps to improve image quality, enhance visibility, and expand dataset variability so that the images were more reasonable for training. Such processes are important for ensuring that you have a clean and varied dataset to train your AI model effectively [19].

1) Image Denoising using Bilateral Filter

Many underwater images contain noise on account of water turbidity and low-light conditions turning out to be irrelevant to the critical features. To investigate this, we applied the bilateral filter, a denoising technuiqe, which efficiently reduces noise while maintaining edges and fine details [20]. Reasonable inputs guarantee that futile artifacts do not get plugged to the model that would adversely affect the learning process.

2) Image Brightness Enhancement using AGCCPF

The environment, in the deep sea where many species of marine life have been observed, has less sun light, therefore more images will have small brightness. Image brightness and contrast enhancement while maintaining colors, as compared in Figure 2, was performed using Adaptive Gamma Correction Color Preserving Framework (AGCCPF) [21]. Using this technique, all of the image is more visible and classifying becomes easier[22].

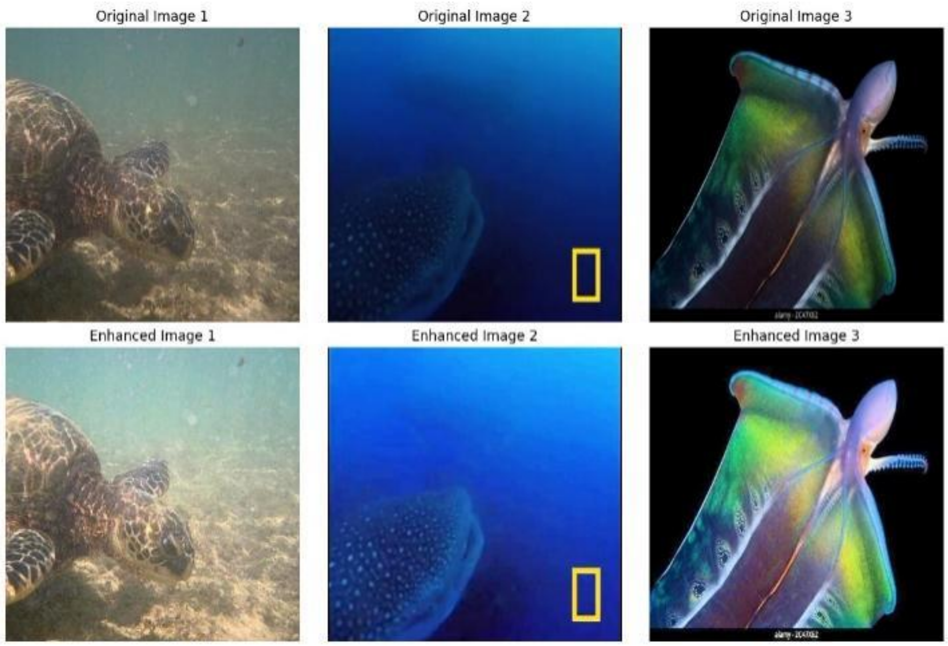

Figure 2: Before and after of image enhancement.

3) **Image Augmentation**

Image augmentations were performed so as to increase diversity in the datasets and thus improve the robustness of the model through rotation, flipping, zooming and translation, amongst other augmentations. In the case of the Blanket Octopus, the original 690 images were augmented to 3,457 , as shown in Figure 3. This is done to enable the model to better generalize by providing a more diverse set in terms of such variations, decreasing the chance of overfitting [23].

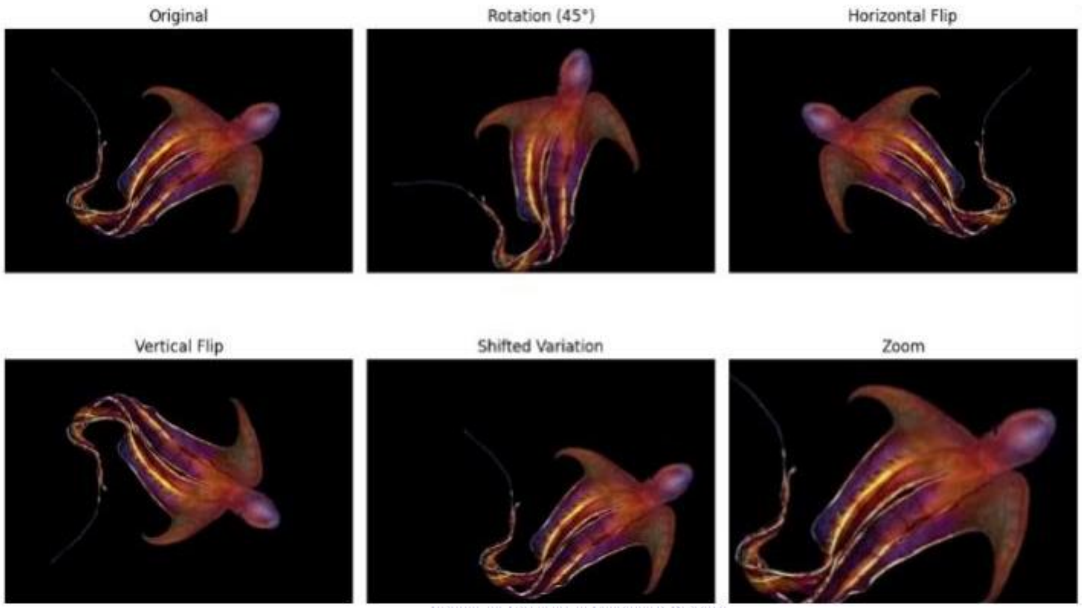

Figure 3: Before and after of image augmentation.

These preprocessing stages guaranteed that the dataset was not just high-quality, but also diverse and reflective of the real-world scenario. This helps improve the accuracy and robustness of the AI model in identifying endangered marine species [24]

C- Data Spiltting

The preprocessed dataset was divided into two parts: 80% training and 20% testing as shown in Figure 4. This division allows the model to learn from a large amount of data but also be thoroughly tested on data not seen . The testing set offers an impartial measure of the model's generalization capacity and overall performance [25].

Xcepforest Methodology

For endangered marine species classification, this research proposes an XcepForest model which integrates Xception for features extraction in addition to a Random Forest (RF) classifier for classification. Incorporating the features from Xception with the classification from ensemble learning of trees is a good fallback that allows for highly accurate and reliable classification. The methodology is centered on three main stages:

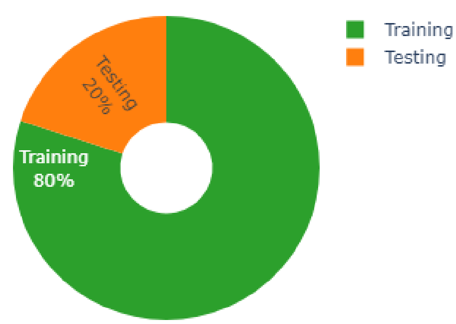

Figure 4: The 80% of dataset was dedicated for training the model , while the rest of 20% was only for testing.

D- Preprocessing of Collected Data

For meaningful visual features, we leverage the Xception network , which uses depth wise separable convolutions in place of the original Inception modules. Xception: Xception is an image isolation model that has shown awesome performance and is pre-trained on ImageNet.

1) **Input Preprocessing:** Images are resized to 480 × 480 pixels as required by Xception.
2) **High-Dimensional Feature Extraction:** The Xception model generates high-dimensional feature maps which you iteratively take the number of top classification layers out.

3) **Feature Reshaping and Flattening:** The feature maps are then reshaped into the flattened one-dimensional feature vectors, ready for feeding into the Random Forest classifier.

E- Classification Using Random Forest

The extracted and flattened feature vectors are then passed into a Random Forest classifier, a powerful ensemble learning method characterized by its robustness, interpretability, and proficiency in processing high-dimensional data.

F- Training and Evaluation

The dataset is split into an 80:20 train-test ratio to allow for robust model evaluation. The training phase includes:

1) **Feature Extraction Stability:**

The Xception model was chosen for this deep-learning-based transfer learning project as it has been shown to generate high-quality features for image-related tasks. The model is frozen during training as the aim is to get higher stability during feature extraction with the help of pre-trained weights [27, 28].

2) **Model Optimization:**

The Random Forest classifier is then optimized using the extracted features .The optimized parameters are shown in Table 2 .

Methodology Workflow

Here, we present the XcepForest model, shown in Figure 5, which harnesses the goodness of the deep learning model of Xception along with the classification strength of ensemble learning model such as Random Forest for building a scalable and efficient solution for classifying endangered marine species. Notably, this method guarantees a high level of precision while providing an easy-to-understand and computationally light framework for marine conservation applications.

Table 2: Optimized Hyperparameter for RF classifier.

Hyperparameter	Value
Number of Estimators (`n_estimators`)	100
Cost-Complexity Pruning (`ccp_alpha`)	0.01
Random State	42

1) **Ensemble Learning:**

The Random Forest is made up of a collection of decision trees, where each one is trained on a random group of features. Trees in random forest are "truly random", so the final prediction is obtained by averaging all trees, which decreases the risk of overfitting and consequently gives us a better prediction[26].

2) **Species Classification:**

The classifier distinguishes among various endangered marine species (e.g., green sea turtles, blanket octopuses, and whale.

Result and Analysis

A- Model Performance

As a solution, we developed the XcepForest model that learns high-dimensional features from our images

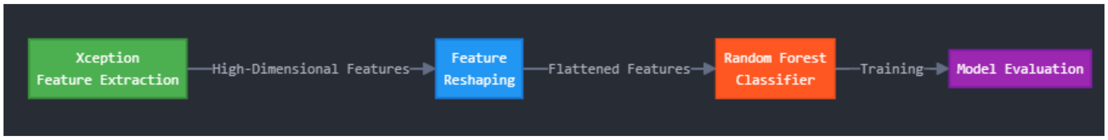

Figure 5: Architecture of the XcepForest Model for Underwater Endangered Species Classification

using a pretrained Xception network and make categorization using a Random Forest classifier as final model on the test dataset for our dataset of endangered marine species. With 92.73% and 92.45% training and testing accuracy (respectively), the model also demonstrates strong generalization ability on both seen and unseen data.

The small difference between the testing and training accuracy implies that XcepForest does not overfit, making it highly reliable and stable for realistic applications. The visual comparison of training and testing accuracy is done in Figure 6 , and the Figure 7 shows the Confusion Matrix of our model .

B- Comparison with Existing Models

To contextualize the performance of XcepForest, the accuracy rates ranging from 87% to 98% reported in marine species classification state-of-the-art models such as YOLOv8, YOLOv7, improved Mask R-CNN were used for comparison.

Although these models have performed well for some applications, they usually require intensive computational resources and suffer from low interpretability in conservation cases. In summary, with respect to both efficiency, accuracy, and interpretability, XcepForest offers a suitable approach for deploying in resource-constrained environments.

C- Analysis of Classification Results

Classification performance by the XcepForest model was consistent among the three target species (green sea turtle, whale shark and blanket octopus). This approach provided good performance given the issues present with underwater images like occluded images and variations in lightings as well as the performability of deep feature extraction from Xception and classification using Random Forest.

These findings suggest that XcepForest can serve as a feasible tool for marine conservation practitioners to correctly identify various species from diverse and complex aquatic ecosystems. Future capabilities could include more endangered species integrations to further biodiversity monitoring.

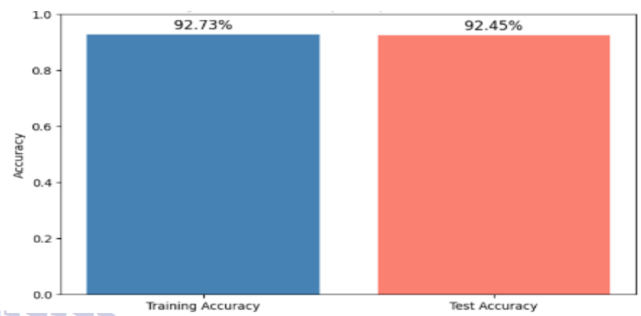

Figure 6: The graph of training accuracy, which was 92.73% and test accuracy which was 92.45

Advanced monitoring tools are needed for the diminishing wildlife of threatened marine species. In this study, we introduced the hybrid deep learning

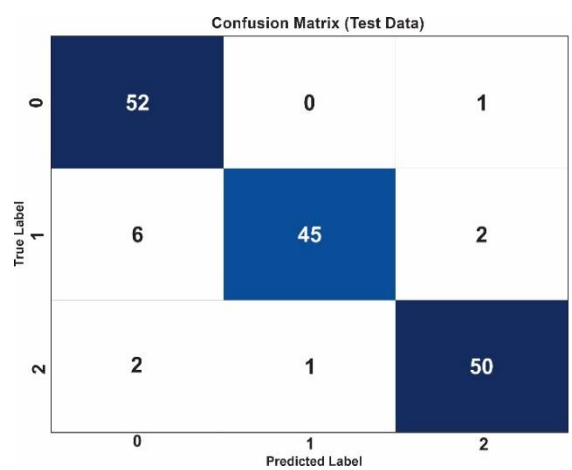

Figure 7: Confusion Matrix of the Model

model, named XcepForest, that combines the feature extraction ability of Xception and classification ability of Random Forest. The model demonstrated an admirable 92.73% accuracy on training data and 92.45% accuracy on testing data, cementing it as a feasible solution for the classification of endangered species of animals like green sea turtles, whale sharks and blanket octopuses.

The main qualities of XcepForest that matter in real-world usage with limited resources and requirements of scalability, interpretability, and efficiency date to its core architecture. This study highlights the usefulness of hybrid models in marine conservation, particularly as they are implemented alongside emerging technologies (e.g., IoT reproduction for real-time species identification).

Future work will expand on the framework with more endangered species and the inclusion of real-time monitoring solutions to support global marine conservation efforts more broadly.

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