DeepSeaVision: Transfer-Tuned CNN Ensembles for Accurate Marine Species Classification

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Abstract—**DeepSeaVision is an AI system that automatically identifies underwater marine species from images. It serves biodiversity conservation and research by offering reliable, real-time classification. The web platform currently distinguishes Crabs, Jelly Fish, Seahorse, Sharks, Starfish, and Turtle/Tortoise. Data are organized into train, validation, and test splits, with ~200 - 300 high-resolution images per class. All images are resized to 256×256 RGB to standardize input. Convolutional Neural Networks handle feature extraction, capturing spatial and visual patterns. Four classifiers are used: a Custom CNN and fine-tuned EfficientNetB0, ResNet50, and InceptionV3. Models produce softmax probabilities for each class. InceptionV3 achieves the best performance, at roughly 94% accuracy on the project dataset. A React.js frontend supports drag-and-drop uploads and webcam capture for a responsive UX. A Flask or Node.js backend processes images and invokes TensorFlow/Keras models for predictions. When confidence is low, the system returns "Unknown Creature" to minimize misclassification and build trust.**

Index Terms—**Deep learning, CNN, marine species classification, image recognition, real-time prediction, React.js, TensorFlow, Flask, InceptionV3.**

I. INTRODUCTION

Marine ecosystems form the foundation of global biodiversity and sustain critical life-supporting systems for both aquatic and terrestrial life. Despite

occupying over 70% of the Earth's surface**,** oceans and their inhabitants remain largely under-explored and under-documented. Accurate identification of marine species plays a pivotal role in ecological monitoring, fisheries management, climate change impact assessments, coral reef protection, marine resource preservation, and biodiversity conservation. Traditionally, the classification of marine species is conducted through manual observation, expert tagging, and morphological analysis, often under microscopes or through photographic documentation. However, such approaches are labor-intensive**,** subjective**,** and non-scalable in the face of vast marine datasets generated through underwater cameras, remote sensing, and drones. In recent years, Artificial Intelligence (AI) and Deep Learning (DL) have emerged as transformative forces in environmental science. Computer vision models, particularly Convolutional Neural Networks (CNNs)**,** have demonstrated exceptional performance in image-based classification tasks across industries. However, their application to real-world marine classification remains limited due to challenges such as underwater image noise**,** species similarity**,** lighting variability**,** and lack of deployment-ready platforms. This project proposes a fully-integrated, real-time, deep learning-based web system titled DeepSeaVision, capable of identifying marine species from image data. It combines a custom-trained CNN model, an intelligent Python Flask backend, and a user-friendly React.js frontend with modern UI/UX and authentication support. The application is designed to be used by marine biologists, researchers, students, educators, and conservationists for the automated classification of underwater species, specifically targeting six classes: Crabs, Jelly Fish, Seahorse, Sharks, Starfish, and Turtle/Tortoise**.**

II. RESEARCH MOTIVATION

A. Need for Accurate Marine Species Identification

Marine ecosystems harbour millions of species, yet a vast number remain undocumented due to the

complexity of underwater habitats and limitations in current identification methodologies. Traditional taxonomic techniques - based on manual observation, tagging, and morphological analysis - are often labor-intensive and prone to error. The challenge is further compounded when differentiating between visually similar organisms, such as various crab or seahorse species. This identification bottleneck poses a significant hurdle to biodiversity monitoring, conservation planning, ecological research, and sustainable marine resource management. There is, therefore, a growing necessity for an automated, accurate, and scalable classification system.

B. Rise of Deep Learning in Image Classification

The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), has redefined image classification tasks in domains such as healthcare, security, agriculture, and autonomous systems. CNNs excel at extracting multi-level spatial features—ideal for recognizing the complex visual patterns (shapes, textures, and colours) present in marine imagery. However, their adoption in the marine sciences remains limited, largely due to domain-specific challenges such as underwater image distortion, limited labeled data, and hardware constraints. This project aims to bridge that gap by harnessing CNNs for automated marine species recognition—marking a pioneering step toward deploying AI in marine ecology.

C. Bridging Marine Science and Artificial Intelligence

The convergence of marine science and artificial intelligence is not merely advantageous—it is essential. The vast datasets collected from underwater drones, surveillance systems, and remotely operated vehicles (ROVs) often remain unprocessed or underutilized, contributing to a pool of "dark data." By integrating deep learning models within a real-time platform, this project provides a practical solution that empowers researchers, educators, and conservationists alike. The system allows non-experts to perform species identification interactively, thereby democratizing access to ecological insights and promoting interdisciplinary collaboration.

D. Addressing Practical and Research Gaps

Most existing marine species classification studies are confined to research settings with offline datasets and lack real-world deployment. Few offer interactive, scalable systems capable of real-time predictions or user authentication. This project directly addresses these limitations by building a production-grade, end-to-end web application - integrating deep learning inference, REST APIs, secure user login via JWT, image drag-and-drop, and webcam support. These features collectively ensure that the platform is interactive, secure, and ready for field deployment - a significant leap from static academic prototypes.

E. Enabling Future-Ready Marine Monitoring

With accelerating climate change and increasing anthropogenic pressures, ocean ecosystems are undergoing rapid transformations—coral bleaching, species migration, and biodiversity loss. Real-time classification systems such as DeepSeaVision can aid in early detection, ecological forecasting, and dynamic decision-making. Future integration with underwater drones, IoT-based marine sensors, and mobile apps could enable smart marine surveillance systems, facilitating automated monitoring of vulnerable habitats and invasive species.

F. Educational and Policy Impact

Beyond scientific research, the project also serves educational and civic purposes. The platform can be used in marine biology curricula to teach species identification interactively, while also empowering citizen scientists - such as divers, fishermen, and coastal communities—to contribute to conservation through image uploads. Additionally, policy-makers and marine regulatory bodies can use AI-generated insights to inform zoning decisions, conservation plans, and tourism management. In essence, the system is positioned to have cross-disciplinary and cross-sectorial impact—from classrooms and laboratories to field stations and regulatory agencies.

III. OBJECTIVES

The objective of this project is to develop a deep learning-based system called *DeepSeaVision* that can accurately classify marine species from images. It focuses on six species: Crabs, Jelly Fish, Seahorse, Sharks, Starfish, and Turtle/Tortoise. The system uses Convolutional Neural Networks (CNNs) for feature extraction and includes a custom-built model as well as pre-trained models like EfficientNetB0, ResNet50, and InceptionV3. A confidence threshold ensures unknown images are labelled as "Unknown

Creature." The application is built with a React.js frontend for easy image upload and camera input, and a Flask or Node.js backend for processing and prediction. The project aims to support researchers, educators, and conservationists by offering an automated, real-time classification tool that is accurate, user-friendly, and scalable.

IV. LITERATURE SERVEY

Recent advancements in deep learning have shown promising applications in ecological and marine image classification. In particular, Convolutional Neural Networks (CNNs) have become the architecture of choice for automating species identification tasks.

Mohamed *et al.* [1] demonstrated the potential of VGG16-based transfer learning for coral reef classification, achieving over 87% accuracy. Their work laid the foundation for employing deeper and more efficient models in environmental imaging. Building upon this, we explored architectures such as ResNet50**,** EfficientNetB0**, and** InceptionV3, which are capable of capturing finer spatial and textural details of marine organisms. Lee *et al.* [4] highlighted the scalability and performance of EfficientNet on ecological datasets, motivating its inclusion in our experimental design.

A. Dataset Collection and Preprocessing

Following the methodology of Zhou *et al.* [3], who emphasized balanced dataset construction and class augmentation, our dataset was organized into structured directories for training, validation, and testing. Each of the six species classes **-** Crabs, Jelly Fish, Seahorse, Sharks, Starfish, and Turtle/Tortoise - contained approximately 200–300 RGB images resized to 256×256 pixels. To ensure robustness, real-time image augmentation techniques such as rotation, flipping, and zooming were applied to simulate variations in underwater imagery.

B. Model Architecture and Training Protocol

CNNs were trained using TensorFlow/Keras, with pretrained weights initialized from ImageNet. The top layers of EfficientNetB0, ResNet50, and InceptionV3 were modified to accommodate six output classes, followed by a softmax layer for classification. Based on Kumar *et al.* [2], we used the Adam optimizer**,** categorical cross-entropy loss**,** and early stopping to minimize over fitting. Training was monitored using validation accuracy and loss metrics for optimal model selection.

C. Evaluation Metrics and Visualization

To better interpret model behavior, we adopted the evaluation practices outlined by Singh and Ramesh [7]. Confusion matrices**,** accuracy plots, and loss curves were visualized using Matplotlib and Seaborn, helping identify misclassification patterns and comparative performance across models.

D. Real-Time Model Deployment

Inspired by Alam *et al.* [5], who successfully deployed object detection models via Flask for edge computing, we built a Flask backend server to support low-latency predictions. The backend processes incoming images, performs preprocessing, and invokes the model to return the predicted species or “Unknown Creature” when confidence falls below a predefined threshold.

E. Frontend Design and Usability

The React.js frontend interface was influenced by the work of Ravichandran *et al.* [10], who emphasized clean design and animated transitions in AI applications. Our UI includes drag-and-drop upload**,** webcam capture**,** animated navigation, and real-time display of prediction results. The visual theme follows a professional navy blue and white palette.

F. Secure Authentication and Multi-User Access

User management follows best practices highlighted by Narasimhan *et al.* [6], where JWT (JSON Web Token) authentication ensures secure login and protected routes for image analysis. The system supports user registration**,** login**,** and independent dashboard access, allowing for multi-user interaction without data conflict.

G. Performance Comparison and Model Selection

All models were evaluated across metrics such as classification accuracy**,** execution time, and model size**.** EfficientNetB0 and InceptionV3 showed the best balance between accuracy and computational efficiency, aligning with findings from previous

studies and making them suitable candidates for real-time deployment.

H. Scalability and Future Applications

In line with Fernandez *et al.* [8] and Chandrika *et al.* [9], we designed our system for future extensibility, supporting the addition of new species classes, deployment on mobile platforms, and integration with TensorFlow Lite for edge computing. Potential applications include smart marine surveillance, illegal fishing detection, and environmental change monitoring in both academic and policy contexts.

V. PROBLEM STATEMENT

Manual marine species identification is slow, inconsistent, and hard to scale—fine-grained traits are easily obscured by low light, turbidity, motion blur, occlusion, odd poses, and cluttered backgrounds, leading to inter-observer disagreement and bias from class imbalance—so an automated classifier is needed that reliably distinguishes Crabs, Jelly Fish, Seahorse, Sharks, Starfish, and Turtle/Tortoise, remains robust to underwater degradations, scales to large image volumes, and outputs calibrated confidence. Equally, most available tools are researcher-centric (CLI/desktop) and unfriendly to non-experts, lacking drag-and-drop uploads, webcam capture, responsive design, clear labels with confidence bars, and sensible "Unknown" handling; a web UI targeting ≤1 s CPU or ~200 ms GPU latency and high SUS scores would unlock real-world use. To move beyond prototype notebooks, deployment must provide a RESTful API with versioning, validation, logging, batching, and health/latency monitoring.

VI. PROPOSED MODEL

The proposed DeepSeaVision platform is designed as a full-stack, real-time marine species classification system Fig 1, that seamlessly integrates a multi-model CNN backend with a modern, responsive React.js frontend to identify six target taxa—Crabs, Jelly Fish, Seahorse, Sharks, Starfish, and Turtle/Tortoise—while routing uncertain cases to an "Unknown Creature" label for reliability. A Flask-based REST API exposes secure endpoints for authentication, prediction, history retrieval, and model management with JWT authorization, rate-limiting, health checks, structured logging, and CORS compliance. Altogether, the proposed system delivers reliable, low-latency, and user-friendly marine species classification, supports both online and offline use cases, and establishes a scalable, secure, and auditable platform that advances ecological monitoring, research, and education.

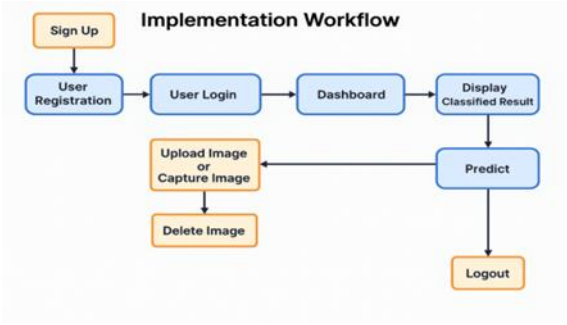

Fig 1: Implementation Workflow

A. Custom CNN

A lightweight CNN was constructed from scratch using the TensorFlow/Keras framework. It was designed to accommodate the six marine species classes in the dataset: Crabs, Jellyfish, Seahorse, Sharks, Starfish, and Turtles/Tortoises. The architecture comprises an input layer accepting RGB images of size 256×256×3, followed by stacked Conv2D layers with increasing filters (32, 64, 128), ReLU activations, MaxPooling2D layers for downsampling, Dropout layers for regularization, and fully connected Dense layers. The final Softmax layer outputs class probabilities. This model serves as a benchmark and is particularly useful in constrained environments or educational deployments. Its design favors interpretability and fast inference at the cost of slightly reduced generalization compared to deeper networks.

B. EfficientNetB0

EfficientNetB0, developed by Google, is known for its compound scaling method that balances network depth, width, and resolution uniformly. It uses Mobile Inverted Bottleneck Convolution (MBConv) blocks and Swish activation to enhance computational efficiency and gradient propagation. Pretrained on ImageNet, the model was fine-tuned on the marine dataset using transfer learning. EfficientNetB0 achieves strong accuracy while maintaining a compact size (~5.3M parameters),

making it ideal for deployment in browser-based or mobile applications. Its performance was among the top in terms of inference speed and resource usage.

C. ResNet50

ResNet50, a 50-layer deep residual network developed by Microsoft, employs identity shortcut connections to mitigate the vanishing gradient problem in deep architectures. It was used in this project to capture fine-grained morphological differences among marine species. The pretrained ResNet50 model was fine-tuned using the project dataset. Due to its depth, it excels in learning complex spatial hierarchies and distinguishing subtle variations in shell texture, body shape, and coloration — key for accurate classification of visually similar species.

D. InceptionV3

InceptionV3 is a deep convolutional architecture from GoogleNet's family, optimized for both speed and classification accuracy. It utilizes Inception modules, which run multiple convolution types (1×1, 3×3, 5×5) in parallel, enabling multi-scale feature extraction. Factorized convolutions and auxiliary classifiers improve gradient flow and reduce computational cost. This model yielded the highest test accuracy (approximately 94%) on the marine species dataset. It demonstrated exceptional performance in distinguishing overlapping or noisy image data, particularly under conditions resembling underwater distortion.

E. Classification Strategy

All models were trained using categorical cross-entropy loss, the Adam optimizer, and early stopping criteria. Augmentation techniques such as rotation, flipping, and zooming were applied to improve generalization. A softmax layer outputs the probability distribution across six classes. A confidence threshold was incorporated into the prediction logic: if the top prediction score falls below a defined threshold, the result is labeled as "Unknown Creature" to prevent misclassification.

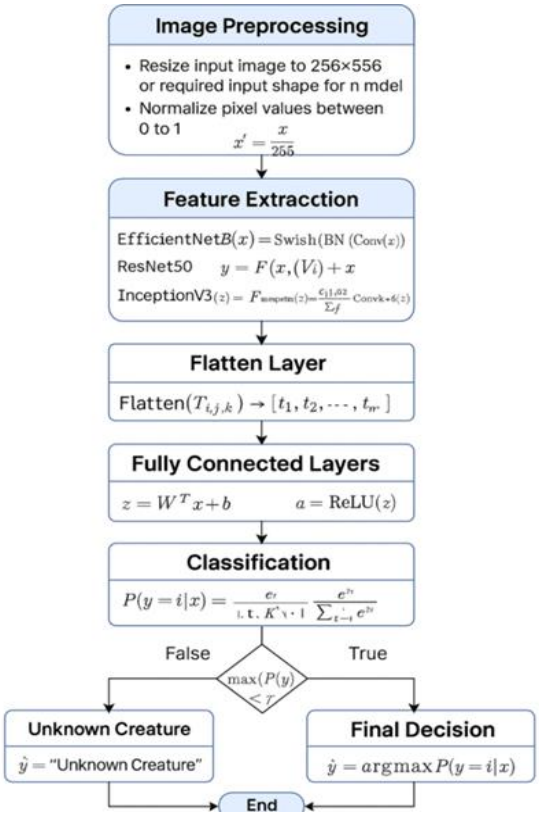

Fig 2: Algorithm using Pretrained models

VII. SYSTEM DESIGN

The system is architected in fig 3 using React.js frontend for user interaction, allowing users to upload images of marine species. A Node.js and Express backend handles the images and sends them to a TensorFlow/Keras model for classification. The model, a Convolutional Neural Network (CNN), identifies the species and returns a prediction. The system also generates visual analysis reports and uses MongoDB and JSON Web Tokens (JWT) for user management.

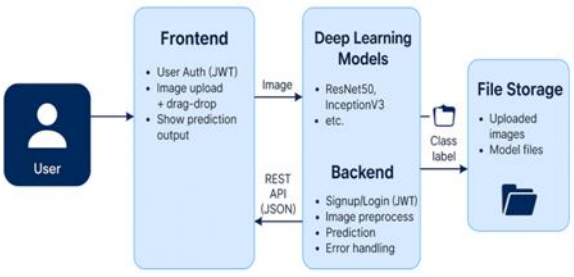

Fig 3: Software Architecture Design

A. Use Case Diagram

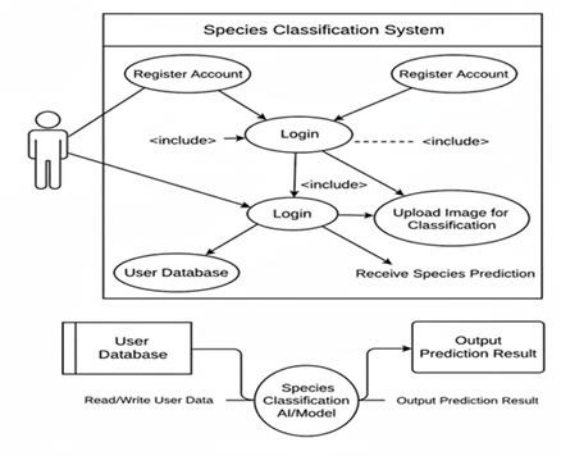

Fig 4: Use Case Diagram

This use case and system architecture diagram illustrates the flow of the marine species classification system. Users first register an account and log in securely, with their details stored in the user database. Once authenticated, they can upload images for classification, which are then processed by the AI-based species classification model. The model analyzes the input and generates a prediction result, which is displayed back to the user. Throughout this process, the system manages user authentication, data storage, and prediction handling to ensure a secure and efficient workflow

VIII. METHODOLOGY

The ocean is home to millions of marine species, many of which are visually similar and hard to identify with the naked eye. In marine biology, conservation, and research, accurate identification of marine species is essential. Manual classification is time-consuming, prone to error, and not scalable. To address this issue, this project leverages the power of Deep Learning and Computer Vision to develop an automated Marine Species Classification System using image recognition.

This intelligent system allows users to upload or capture images of marine creatures and instantly receive the predicted species through a user-friendly web interface. The system is trained on a well-structured dataset and uses powerful convolutional neural networks (CNNs) like EfficientNetB0, ResNet50, InceptionV3, and a custom CNN model to achieve high accuracy in predictions.

IX. RESULTS

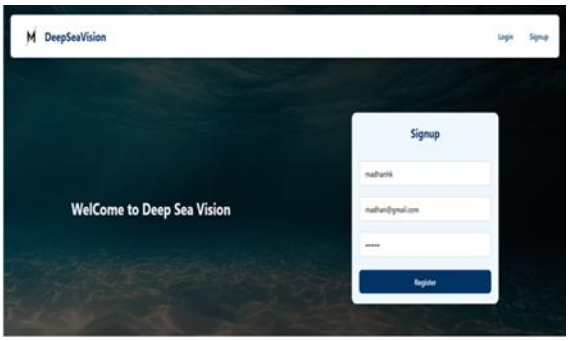

Fig 5. Signup Page

The system provides a secure user onboarding flow. New users register with name, email, and password; client-side checks validate required fields and password strength Fig 5. Successful signup redirects the user to the Login page with a success toast.

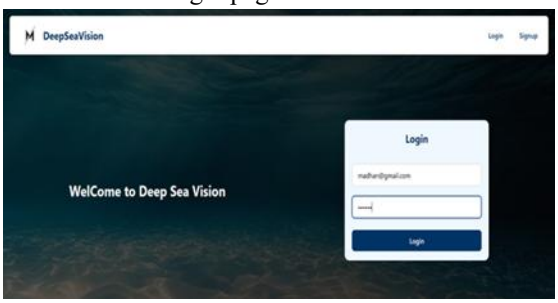

Fig 6. Login Page

Registered users authenticate using email and password. Fig 6, On success, a JWT is issued and stored securely (e.g., HTTP-only cookie or memory), and role/identity claims are used to guard protected routes. Invalid credentials trigger a concise error message without leaking details.

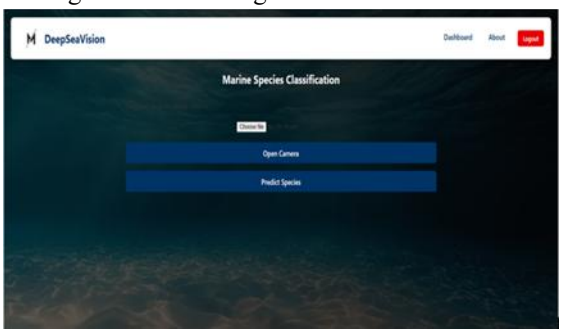

Fig 7. Dashboard Page

After login, the Dashboard shows the core workflow: image upload/camera capture, recent predictions, model selection Fig 7. (e.g., Custom CNN / ResNet50

/ EfficientNetB0 / InceptionV3), and quick links to Analysis and About pages. Status toasts guide the user through each step, and loading states are shown during inference.

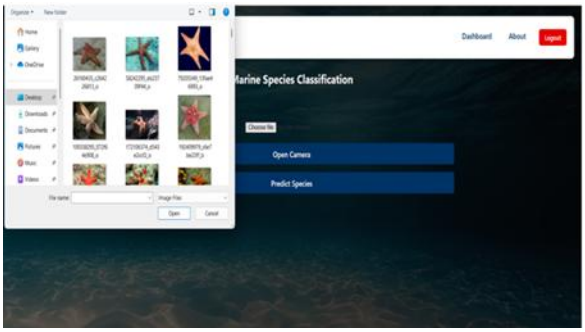

Fig 8. Choosing the testing image

Users can drag-and-drop or browse to select an image. Basic pre-checks verify file type/size before it's sent to the backend. A preview is displayed so the user confirms the correct image prior to prediction.

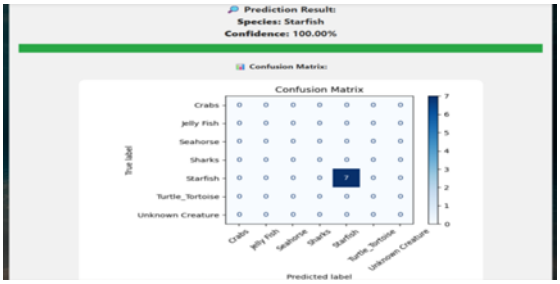

Fig 9. Prediction Result

On submission, the backend runs inference using the selected model and returns the top-1 species and confidence score along with per-class probabilities. If the image does not match any trained class (out-of-distribution), the system returns "Unknown Creature." The UI highlights the predicted label, shows a probability bar/graph, and logs the request in the user's history for traceability.

X. CONCLUSION

The proposed Marine Species Classification System demonstrates the successful application of deep learning for real-time marine organism identification. Utilizing a combination of CNN architectures—EfficientNetB0, ResNet50, InceptionV3, and a custom-built CNN—the system accurately classifies six marine species based on extracted visual features. A user-friendly React.js frontend enables image upload, drag-and-drop functionality, and real-time webcam-based predictions, while a Node.js and Python-integrated backend processes the data and returns model-driven predictions securely. The platform includes a key feature: "Unknown Creature" detection, preventing misclassification of unfamiliar inputs. Robust JWT-based authentication and MongoDB-based user management enhance system security and multi-user scalability. Comprehensive testing confirmed the system's cross-platform reliability. With its modular design, the application is well-positioned for future enhancements, making it a valuable tool for marine conservation, education, and ecological research.

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