# AN APPROACH TOWARDS MARINE ANIMAL DETECTION AND RECOGNITION WITH ADVANCED DEEP LEARNING MODELS

**A PROJECT REPORT**

***Submitted by,***


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***Under the guidance of,***


**Dr. SASIDHAR BABU SUVANAM**


***in partial fulfillment for the award of the degree of***

**BACHELOR OF TECHNOLOGY**

**IN**

**COMPUTER ENGINEERING**
**[Artificial Intelligence and Machine Learning]**

**PRESIDENCY UNIVERSITY**

**BENGALURU**

**JANUARY 2024**

# PRESIDENCY UNIVERSITY

## SCHOOL OF COMPUTER SCIENCE ENGINEERING & INFORMATION SCIENCE

## CERTIFICATE

This is to certify that the Project report **"An Approach Towards Marine Animal Detection and Recognition Using Advanced Deep Learning Models"** being submitted by "Nikitha Vinod, Annapureddy Nehareddy, Reddy Rani Chandan, G.Srinivas" bearing roll number(s) "20201CEI0034 , 20201CEI0048, 20201CEI09050, 20201CEI0029 " in partial fulfilment of requirement for the award of degree of Bachelor of Technology in Computer Engineering[Artificial Intelligence and Machine Learning] is a bonafide work carried out under my supervision.

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## DECLARATION

We hereby declare that the work, which is being presented in the project report entitled **An Approach Towards Marine Animal Detection and Recognition Using Advanced Deep Learning Models** in partial fulfilment for the award of Degree of **Bachelor of Technology** in **Computer Engineering [Artificial Intelligence and Machine Learning]**, is a record of our own investigations carried under the guidance of **Dr. Sasidhar Babu Suvanam, Professor, School of Computer Science Engineering & Information Science, Presidency University, Bengaluru.**

We have not submitted the matter presented in this report anywhere for the award of any other Degree.

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# ABSTRACT

Marine ecosystems are vital components of our planet, housing a diverse array of species. Monitoring and understanding these ecosystems are essential for conservation efforts and scientific research. This paper presents a novel approach to detection and recognition of marine animals using advanced deep learning models, specifically Mobile Net and ResNet-50, in the context of underwater image analysis. Over the past few years, there have been substantial advancements in computer vision tasks thanks to the progress made in deep learning, and its application to marine biology presents promising opportunities. Mobile Net and ResNet-50 are chosen for their efficiency and accuracy, making them suitable for real-time deployment in underwater environments. The proposed system employs a two-step process: object detection and species recognition. Firstly, Mobile Net is utilized for object detection to locate marine animals in underwater images. Next, ResNet-50 is applied for fine-grained species recognition, classifying the detected animals into specific categories. The model is trained on a comprehensive dataset comprising diverse marine species to ensure robust performance. Our experiments demonstrate the effectiveness of the approach in accurately detecting and recognizing marine animals across various underwater conditions, including low visibility and different lighting conditions. The system's performance is evaluated in terms of detection accuracy, species classification accuracy, and computational efficiency. This research makes a valuable contribution to the field of marine biology by offering a dependable and effective tool for the monitoring and study of marine life. The proposed deep learning-based system can assist researchers, conservationists, and marine biologists in cataloging and understanding marine ecosystems, ultimately supporting conservation efforts and advancing our knowledge of these critical environments.

***Keywords*— deep learning, mobile net, resnet-50, image processing, marine animals, deep oceans**

# ACKNOWLEDGEMENT

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# CHAPTER-1

# INTRODUCTION

## 1.1 Motivation

Detection and recognition of marine animals using advanced deep learning models is motivated by the critical need to protect and preserve fragile aquatic ecosystems. These models enable automated monitoring of marine life, aiding in species conservation and biodiversity research. Additionally, they contribute to maritime safety by identifying potential hazards such as large marine mammals near shipping routes. Moreover, understanding marine populations and their behavior can inform sustainable fisheries management and support ecological balance. This technology not only advances our scientific knowledge but also reinforces our commitment to responsible stewardship of the oceans, safeguarding these vital resources for future generations.

## 1.2 Problem Statement

The problem statement for detection and recognition of marine animals using advanced deep learning models is to develop a robust and accurate system for automatically detecting and recognizing marine animals in underwater environments employing advanced deep learning techniques. This system should be capable of processing large volumes of underwater imagery and video data, identifying various species of marine animals, and distinguishing them from other objects and background noise. The goal is to aid researchers, conservationists, and marine biologists in monitoring and studying marine ecosystems, tracking population dynamics, and assessing the health of underwater environments.

## 1.3 Project Introduction

The world's oceans are teeming with diverse and magnificent marine life, from graceful dolphins to majestic whales, and from vibrant coral reefs to intricate schools of fish. Understanding, monitoring, and protecting these ecosystems are critical tasks for scientists and conservationists. A significant challenge in this undertaking involves effectively detecting and recognizing marine animals within their natural environment. The emergence of deep learning and artificial intelligence has transformed the landscape of computer vision, empowering us to create sophisticated tools for automated detection and recognition of marine animals. In this context, Mobile Net ResNet-50, an advanced deep learning model has surfaced as a potent tool for this objective. This model combines the efficiency of Mobile Net with the accuracy of ResNet-50, making it an ideal choice for marine animal detection and recognition. In this research journey, we will explore the depths of deep learning, computer vision, and marine biology to create a powerful tool for the preservation of our oceans. By combining the capabilities of Mobile Net ResNet-50 with the beauty and complexity of marine life, we hope to contribute to a brighter and more sustainable future for our planet's underwater ecosystems.

The topic of "Detection and Recognition of Marine Animals using Advanced Models in Deep Learning" is chosen due to its critical importance in marine conservation and ecological research. Oceans house a diverse range of species, many of which are endangered or understudied. Advanced deep learning models can revolutionize our ability to monitor and protect these animals by automating the identification process, making it more efficient and accurate. This research has the potential to significantly contribute to marine biodiversity preservation, ecosystem health assessment, and the development of informed conservation strategies, ultimately helping us better understand and safeguard the delicate balance of marine ecosystems in the face of environmental challenges.

# CHAPTER-2

# LITERATURE SURVEY

## 2.1 Related Work

**2.1.1** Real-Time Detection Algorithm of Marine Organisms Based on Improved OLOv4-Tiny:

*Yanli Shi ; Ziran Gao ; Sha Li*

In this paper they have proposed a MODA (Marine Organism Detection Algorithm) based on an improved YOLOv4-tiny marine organism detection algorithm. Provide a brief overview of traditional object detection methods and their limitations. Introduce the concept of deep learning-based object detection and its advantages. Real-Time Processing: YOLOv4-Tiny is designed to be computationally efficient, making it suitable for real-time applications. The algorithm achieves real-time performance, it can be valuable for applications such as monitoring marine environments, studying marine life behavior, or even assisting in navigation and safety in real-time. YOLOv4-Tiny is a lightweight model designed for real-time applications, but it may lack the capacity to capture complex features of diverse marine organisms. This limitation could result in lower accuracy, especially for smaller or less common species. Data Scarcity and Diversity: Marine organism datasets may be limited in size and diversity, making it challenging for the model to generalize well to various species, poses, and environmental conditions.

**2.1.2** Deep learning based deep-sea automatic image enhancement and animal species classification:

*Damianos Chatzievangelou ; Jacopo Aguzzi ; Vanesa Lopez- Vazquez ; Jose Manuel Lopez-Guede*

In this work, they have proposed an image enhancement and classification pipeline that allows automated processing of images from benthic moving platforms. Provide an overview of the importance of studying deep-sea environments and the challenges training. Limited availability of deep-sea images, especially for rare or less-studied species, can hinder the model's ability to generalize. Deep learning models, particularly deep neural networks, are often considered as "black-box" models, making it challenging to interpret the decision-making process. Understanding why a model classifies a certain species in a specific way may be difficult.

**2.1.3** Fast Accurate Fish Recognition with Deep Learning Based on a Domain-Specific Large-Scale Fish Dataset:

*Yuan Lin ; Zhaoqi Chu ; Jari Khorhonen ; Min Liu*

Most publicly accessible fish datasets have small-scale and low resolution, imbalanced data distributions, or limited labels and annotations. In this work they have overcome these challenges. Review existing literature on deep learning techniques applied to fish recognition. Discuss various architectures, such as CNNs (Convolutional Neural Networks) or more advanced architectures like ResNet, and their effectiveness. Discuss real-world applications of fish recognition using deep learning models. Highlight how fast and accurate fish recognition can contribute to various fields, including environmental monitoring, fisheries management, and biodiversity conservation. Utilizing a domain-specific large-scale fish dataset allows deep learning models to achieve high accuracy in fish recognition. The model can learn intricate features specific to fish species, leading to more precise classification results. Training on a large-scale dataset helps the model generalize well to various fish species and environmental conditions. This is crucial for the deployment of the model in real-world scenarios where the diversity of fish species and environmental factors can be significant. Fast and accurate fish recognition is achievable with deep learning, especially when using advanced architectures and optimization techniques. This speed is important for applications such as underwater robotics or monitoring systems where quick decision-making is required.

**2.1.4** Machine Learning and Image Processing Methods for Cetacean Photo Identification:

*Rosalia Maglietta ; Roberto Carlucci ; Carmelo Fanizza ; Giovanni Dimauro*

This paper highlights that interest has been increasing in recent years and several intelligent systems have been presented. However, there are still some open questions, and further efforts to develop more effective automated systems. Machine learning facilitates the analysis of cetacean behaviour by automatically associating identified individuals with their behavioural patterns. This helps researchers gain insights into social structures, migration patterns, and other aspects of cetacean behaviour. Efficient cetacean photo identification supports conservation efforts by providing data for the assessment of population health, identifying critical habitats, and informing policies for the protection of these marine species. Machine learning enables the temporal analysis of cetacean photo datasets, allowing researchers to study changes in individual markings over time. This can be valuable for understanding life histories and the impact of environmental factors.

### **2.1.5** Future Trends and Short-Review on Fish Species Classification Models Based on Deep Learning Approaches

*M Bhanumati ; B. Arthi*

Summarize existing literature on deep learning architectures applied to fish species classification. for this task. Highlight prominent models, such as CNNs (Convolutional Neural Networks), ResNet, or other specialized architectures. Briefly discuss traditional methods used for fish species classification. Highlight the limitations of traditional approaches, such as manual identification and low scalability. Deep learning models can automatically learn relevant features from raw data, reducing need for manual feature engineering. These models can adapt to diverse and complex patterns within fish species, making them suitable for a wide range of environment. With appropriate training data, deep learning models can generalize well to unseen examples, enhancing their applicability. Automation of fish species classification tasks can lead to significant efficiency improvements in monitoring and conservation efforts.

# CHAPTER-3

# RESEARCH GAPS OF EXISTING METHODS

## 3.1 Existing System

In the existing methods finding the marine animals classification become very difficult by using deep learning algorithms such as Mobile net Because of manual feature extraction from images is bit complexity and accuracy. To overcome this accuracy issues, we go for the proposed system.

## 3.2 Gaps in the system

**Lack of User-Friendliness:** The current system exhibits poor user-friendliness due to sluggish data retrieval and inefficient data maintenance**.**

**Challenges in Report Generation:** The need for extensive calculations to generate reports results in their production at the end of the session, limiting the model's opportunities to enhance its accuracy.

**Manual Oversight:** The manual execution of all calculations for report generation increases the likelihood of errors.

**Excessive Paperwork:** The current system involves a significant amount of paperwork, and the loss of a single register or record can lead to challenging situations as all documents are essential for report generation.

**Time-Intensive Process:** Since all tasks are carried out manually, generating a report in the middle of a session or as per specific requirements is impractical due to the considerable time it consumes.

# CHAPTER-4
# PROPOSED METHODOLOGY

In the existing methods finding the marine animal classification become very difficult by using deep learning algorithms such as Mobile net Because of manual feature extraction from images is bit complexity and accuracy. To overcome this accuracy issues, we go for the proposed system.

## 4.1Mobile Net architecture

Convolutional Neural Networks (CNNs) have gained immense popularity in the field of computer vision, yet the pursuit of higher accuracy has led to the development of deeper and more intricate models. Unfortunately, such complex networks pose challenges for real-world applications like robotics and self-driving cars due to their computational demands. To address this issue, MobileNet emerges as an efficient and portable CNN architecture designed for practical deployment.

MobileNet stands out by utilizing depth-wise separable convolutions, a departure from the conventional convolutions used in earlier architectures. This strategic choice results in lighter models that are well-suited for resource-constrained environments. By introducing two innovative global hyperparameters, namely width multiplier and resolution multiplier, MobileNets offer model developers the flexibility to balance trade-offs among latency, accuracy, and size. This allows them to customize the architecture according to specific speed and space requirements.

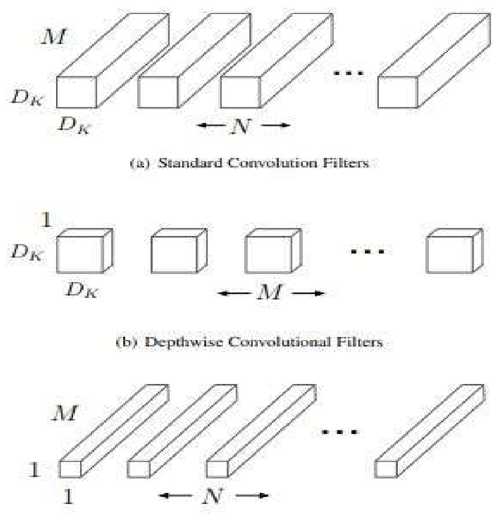


**Figure 4.1.MobileNet Architecture**

### 4.1.1 Standard Convolution layer

The individual standard convolution unit (represented as Conv in the table above) is depicted as follows

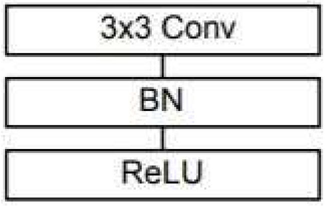


**Table 4.1.Standard Convolution**

### 4.1.2 Depth wise separable Convolution layer

A singular Depth-wise separable convolution unit (indicated as Conv dw in the aforementioned table) is depicted as follows

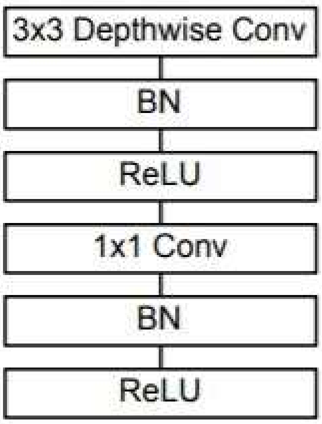


**Table 4.2.Depthwise Layer**

### 4.1.3 Width Multiplier

The width multiplier, represented by α, serves as a global hyperparameter crucial for creating more compact and computationally efficient models. Ranging between 0 and 1, α allows the adjustment of model size and computational complexity. Given a layer and a specific α value, the input channels 'M' are scaled to α * M, and the output channels 'N' are scaled to α * N. This scaling effectively reduces the computational cost and overall model size, albeit at the expense of performance. The decrease in computation cost and parameter count is roughly proportional to the square of α. Frequently employed values for α include 1, 0.75, 0.5, and 0.25.

### 4.1.4ResolutionMultiplier

The second key parameter introduced in Mobile Nets is known as the resolution multiplier, denoted by ρ. This hyperparameter plays a role in diminishing the resolution of the input image, consequently reducing the input size for each layer by a consistent factor. Precisely, with a specified value of ρ, the input image resolution is modified to 224 * ρ. This adjustment results in a proportional reduction in computational cost by a factor of ρ^2.

## 4.2 ResNet50

ResNet50 is a convolutional neural network characterized by its impressive depth of 50 layers. Developed and trained by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in 2015, the details of its model performance can be found in their paper titled "Deep Residual Learning for Image Recognition." Trained on over 1 million images from the ImageNet database, ResNet50 shares similarities with VGG-19 as it is capable of classifying up to 1000 objects. The network's training involves 224x224 pixels colored images, showcasing its versatility in image recognition tasks. For a quick overview, ResNet50's compact size and high performance make it a noteworthy model in the realm of deep learning.

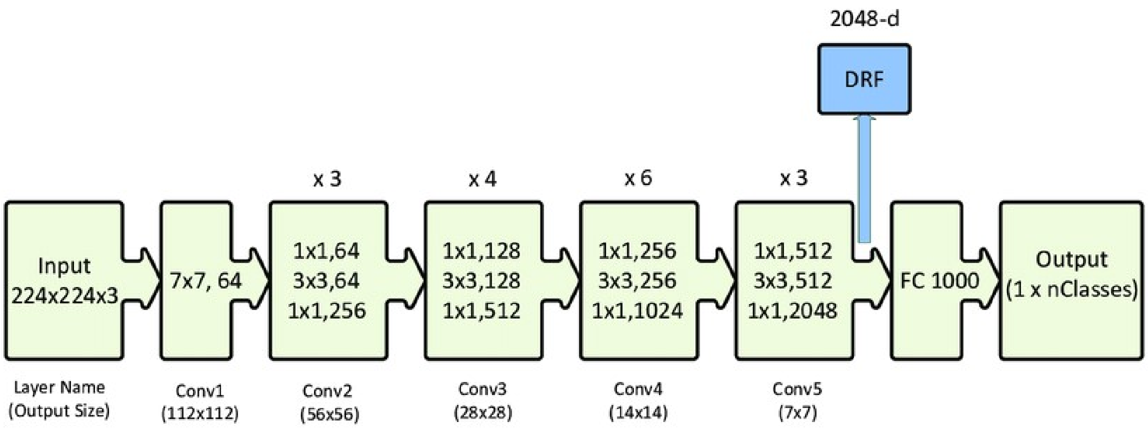


**Figure 4.2. ResNet50 Architecture**

# CHAPTER-5
# OBJECTIVES

The aim of the project is,

- cutting-edge system for the automated identification and tracking of marine animals in their natural habitats.
- support conservation efforts and promote sustainable practices in the maritime industry.
- creation of a robust and accurate deep learning model capable of detecting various marine species from images and videos, enabling real-time monitoring of their populations.

# CHAPTER-6
# SYSTEM DESIGN & IMPLEMENTATION

### 6.1 Introduction of Input Design

In the context of an information system, input denotes the raw data that is processed to produce output. During the input design phase, developers must thoughtfully consider the choice of input devices, including PCs, MICR, OMR, and others.

Consequently, the caliber of the system's output is contingent upon the type or quality of input. Input forms and screens that are skillfully designed showcase the following characteristics:

- They should efficiently serve a designated purpose, such as storing, recording, and retrieving information.
- Ensuring accurate and thorough completion is a priority.
- Simplicity and ease of filling out are key considerations.
- Prioritizing the user's focus, maintaining consistency, and ensuring simplicity are of utmost importance. Achieving these goals involves applying fundamental design principles related to –
    - What inputs are required for the system?
    - How end users react to various components of forms and screens?

Objectives for Input Design

The goals of input design include

• Developing procedures for entering and inputting data

• Reducing the amount of input.

• Generating source documents for data capture or employing alternative data capture methods.

• Creating input data records, data entry screens, user interface screens, etc.

• Executing validation checks and establishing strong input controls.

**6.2 Output Design**

Designing the output stands as a crucial task in any system. In the output design phase, developers identify the necessary output types and meticulously consider the crucial output controls and prototype report layouts.

Objectives of Output Design:

The goals of input design include::

• Developing an output design that serves its intended purpose and avoids generating unnecessary results.

• Developing an output design aligned with the end user's specifications.

• Ensuring the delivery of the correct volume of output.

• Formatting the output appropriately and directing it to the designated recipient.

• Ensuring timely availability of the output for informed decision-making.

**6.3 UML Diagrams**

**6.3.1 Use Case Diagram**

In the Unified Modeling Language (UML), a use case diagram is a behavioral representation derived from the analysis of use cases. Its function is to provide a visual depiction of a system's functionality, showcasing actors, their goals (represented as use cases), and any interconnections among those use cases. The main goal of a use case diagram is to delineate the system functions executed for each actor, concurrently presenting a representation of the roles assumed by actors within the system.

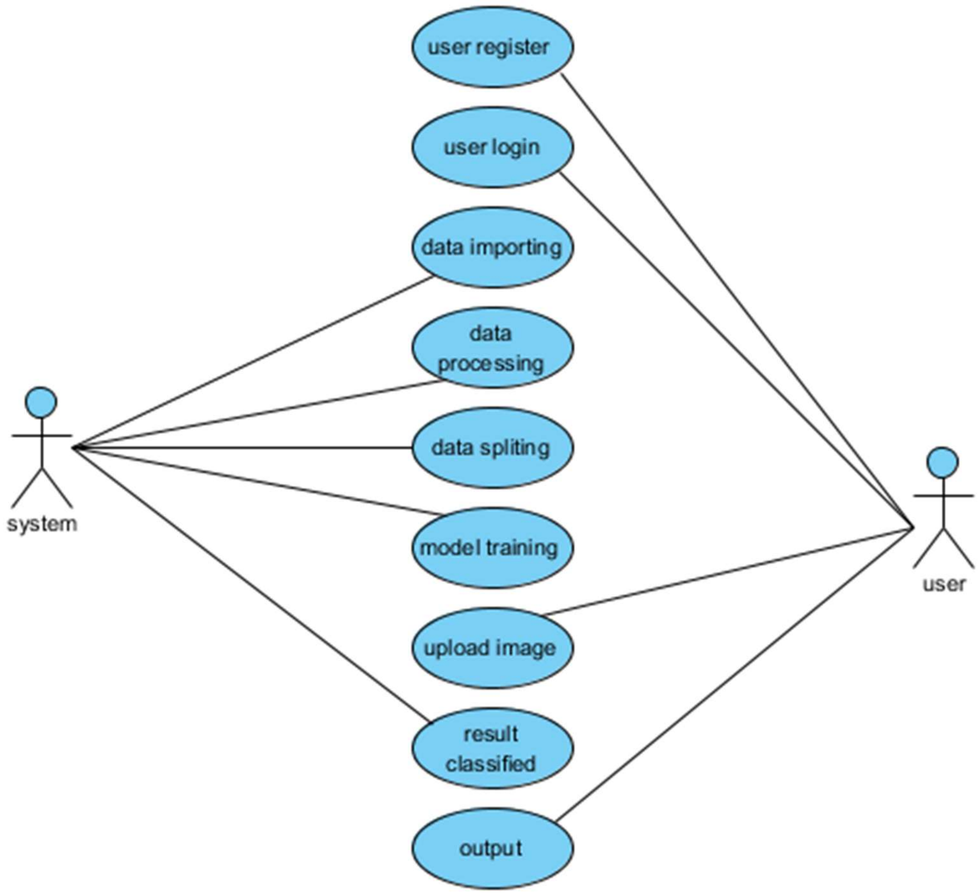


**Figure 6.1.Usecase Diagram**

### 6.3.2 Class Diagram

In the field of software engineering, a class diagram in the Unified Modeling Language (UML) is a static structure diagram that illustrates the structure of a system. It accomplishes this by showcasing the classes of the system, detailing their attributes, operations (or methods), and the relationships between these classes. The diagram elucidates the allocation of information within classes, offering insights into how the system is organized.

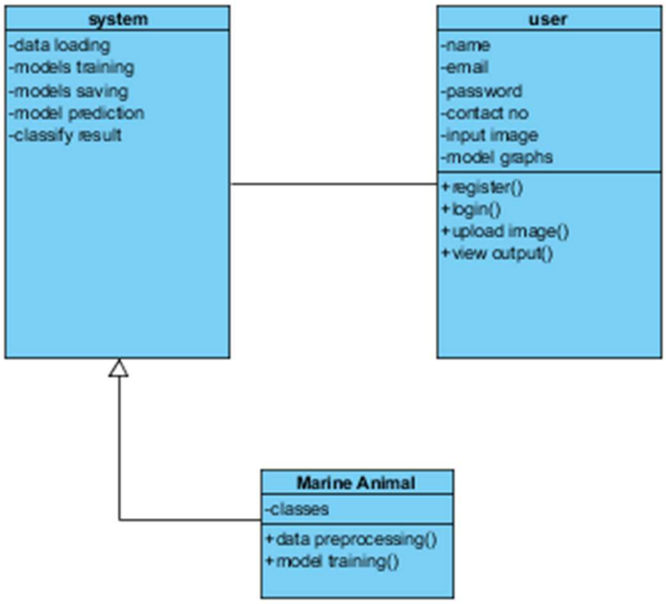


**Figure 6.2.Class Diagram**

### 6.3.3 Sequence Diagram

In the Unified Modeling Language (UML), a sequence diagram serves as an interaction diagram depicting the sequential flow of operations between processes. Derived from a Message Sequence Chart, it provides insights into how processes collaborate and the specific order in which they operate. Sequence diagrams may also be referred to as event diagrams, event scenarios, or timing diagrams.

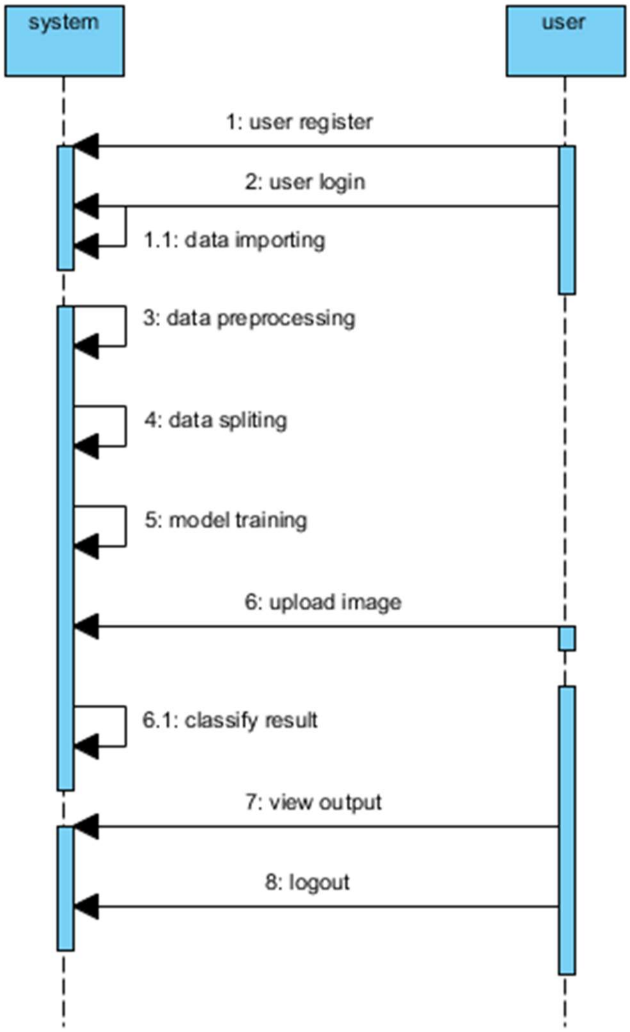


**Figure 6.3.Sequence Diagram**

### 6.3.4 Collaboration Diagram

In the context of a collaboration diagram, sequence of method calls is denoted using a numbering technique, as illustrated below. This numbering system signifies the order in which methods are invoked. Using the example of the system for managing orders, we can explain the collaboration diagram, where method calls resemble those in a sequence diagram. The key distinction lies in the fact that while a sequence diagram does not detail the arrangement of objects, a collaboration diagram explicitly illustrates the object arrangement.


**Figure 6.4.Collaboration Diagram**

### 6.3.5 Deployment Diagram

The deployment diagram portrays the system's deployment perspective and maintains a connection with the component diagram. This linkage arises from the fact that deployment diagrams are instrumental in deploying components. In essence, a deployment diagram comprises nodes, which represent the physical hardware entities utilized for deploying the application.

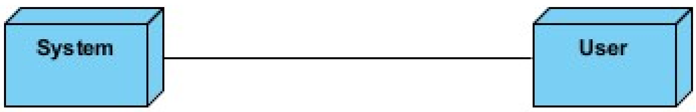


**Figure 6.5 Deployment Diagram**

### 6.3.6 Activity Diagram

Activity diagrams function as visual representations of step-by-step workflows, portraying activities and actions, and incorporating elements like choice, iteration, and concurrency. In the Unified Modeling Language (UML), activity diagrams are valuable for visualizing the sequential workflows of business and operational components within a system. These offer a comprehensive portrayal of the overall control flow.

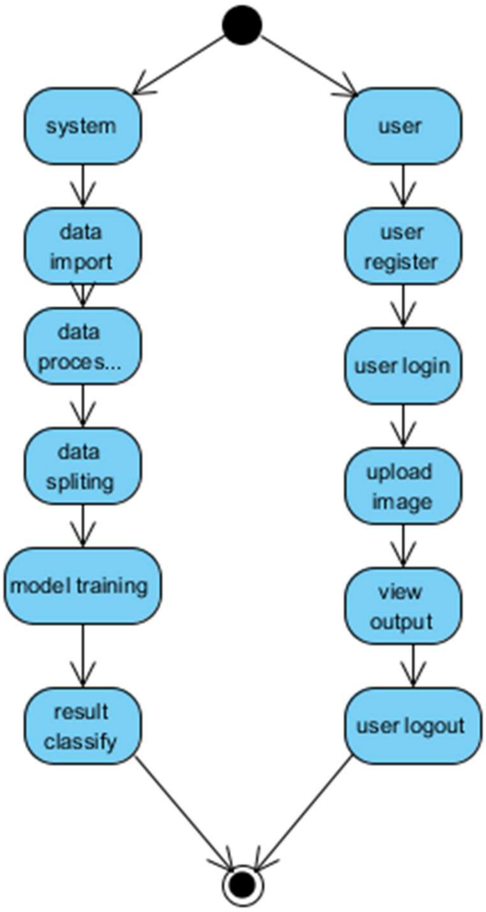


**Figure 6.6.Activity Diagram**

### 6.3.7 Component Diagram

A UML component diagram, often known simply as a component diagram, illustrates the layout and relationships of physical components in a system. These diagrams are often created to aid in modeling implementation details, ensuring that all necessary functions required by the system are appropriately addressed in the planned development process.

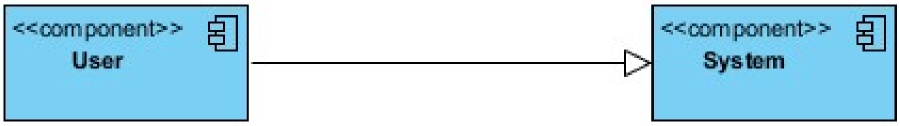


**Figure 6.7.Component Diagram**

### 6.3.8 ER Diagram

The Entity-Relationship model (ER model) delineates the structure of a database using a visual representation known as an Entity Relationship Diagram (ER Diagram). Serving as a design or blueprint, the ER model is a conceptual framework that can be implemented as an actual database. Its key components include entity sets and relationship sets.

The ER diagram showcases the relationships among sets of entities, where an entity set signifies a collection of similar entities, each having attributes. In the realm of Database Management Systems (DBMS), an entity corresponds to either a table or an attribute within a table in the database. Illustrating relationships among tables and their attributes, the ER diagram offers a comprehensive representation of the logical structure of a database. Let's examine a basic ER diagram to understand this concept.

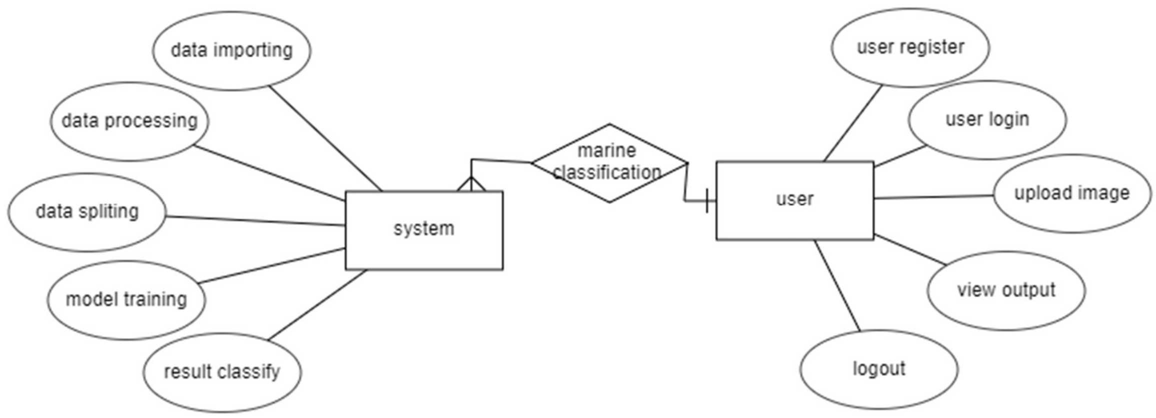


**Figure 6.8.ER diagram**

## 6.4 DFD Diagram

A Data Flow Diagram (DFD) is a traditional approach to visually represent information flows in a system. A well-structured and clear DFD can visually depict a substantial portion of the system requirements. Whether manual, automated, or a combination of both, it showcases the flow of information into and out of the system, identifies transformation points, and indicates storage locations for information. The main goal of a DFD is to outline the comprehensive scope and boundaries of a system. Functioning as a communication tool between a systems analyst and any involved party in the system, it acts as an initial reference for system redesign.

## Zero level Diagram

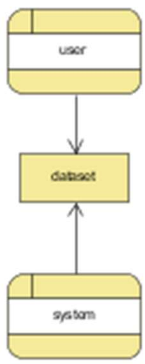


**Figure 6.9.Zero Level**

## Level 1 Diagram

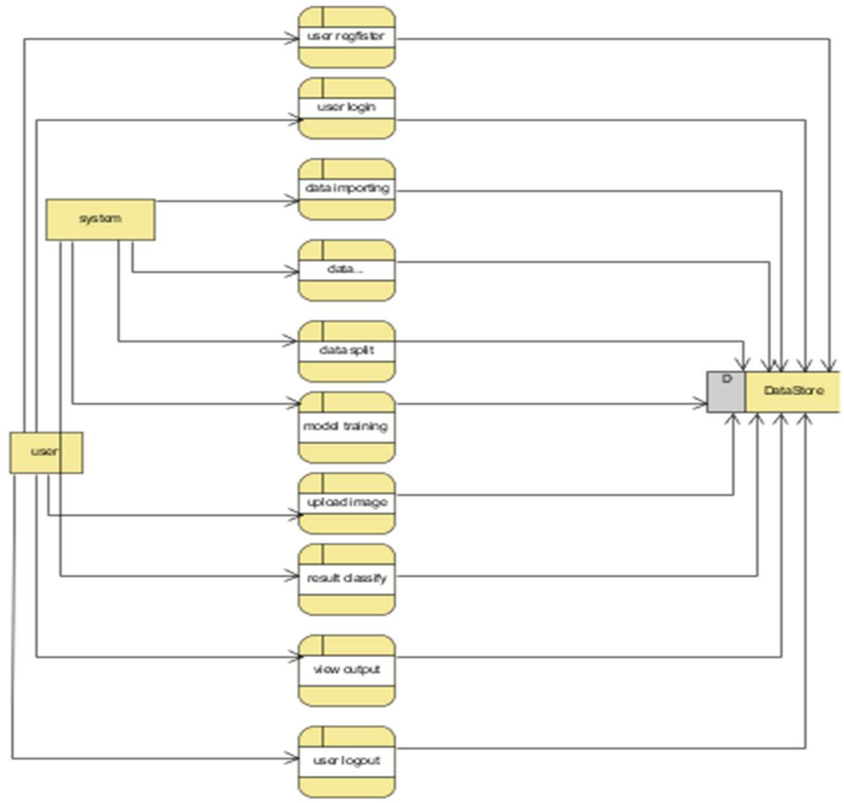


**Figure 6.10.Level 1**

## Level 2 Diagram

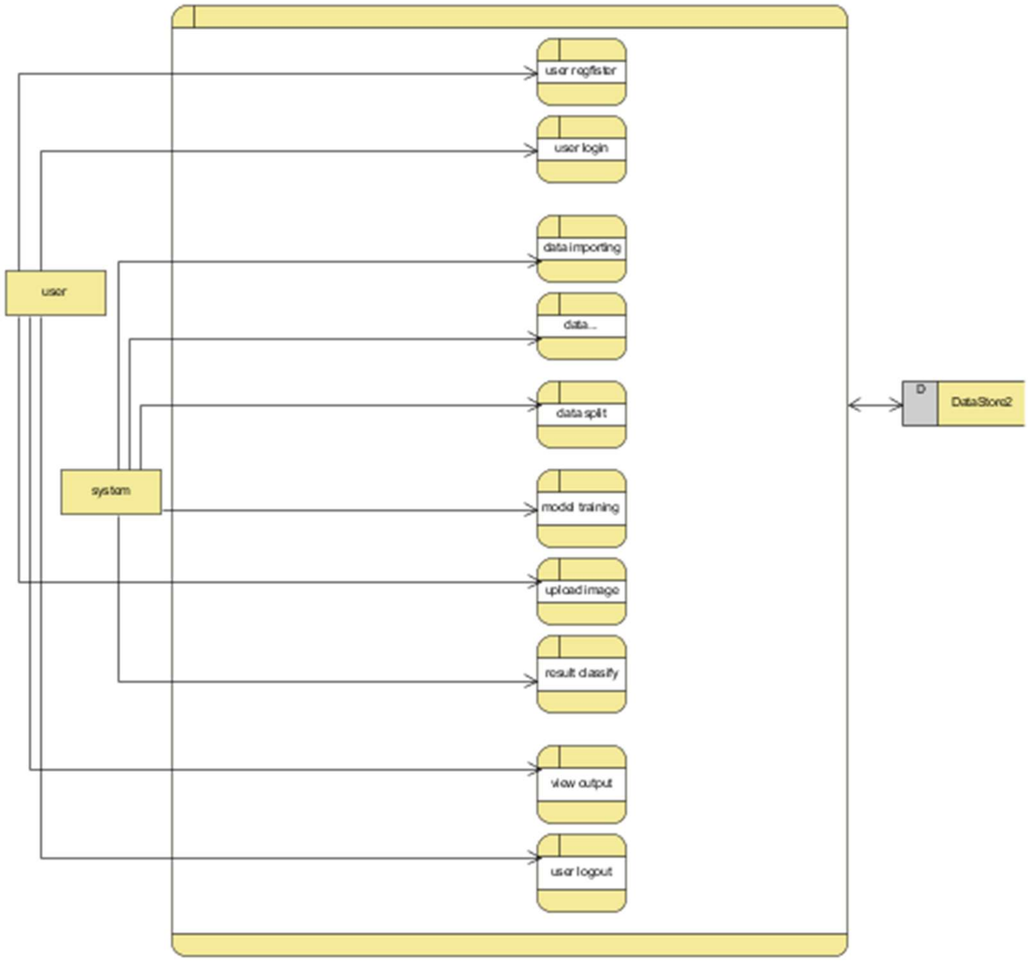


**Figure 6.11.Level 2**

# CHAPTER-7

# TIMELINE FOR EXECUTION OF PROJECT

# (GANTT CHART)

| | Sept 09-Sept 13 | Nov 6 -Nov 10 | Nov 27 -Nov 30 | Dec 26 - Dec 30 | Jan 8 - Jan 12 |
|---|---|---|---|---|---|
| Review 0 | Title Finalization Literature Survey Finalizing objectives Deciding the methodology | | | | |
| Review 1 | | Research and design | | | |
| Review 2 | | | Coding,Collecting dataset& Image processing | | |
| Review 3 | | | | Here add Training the model and Applying Algorithm | |
| Review 4 | | | | | Live Demonstration of the project |

**Table 7.1. Gantt Chart**

# CHAPTER-8
# OUTCOMES

- **Improved Conservation Efforts:** The use of advanced deep learning models can contribute to more accurate and efficient monitoring of marine animals. This can aid in conservation efforts by providing better data on population dynamics, migration patterns, and behavior.

- **Early Detection of Threats**: Deep learning models can be trained to recognize unusual behaviors or anomalies that may indicate potential threats to marine animals, such as illegal fishing activities, pollution, or other environmental hazards.

- **Data Collection and Analysis**: The project may lead to the development of systems capable of automated data collection from various sources, including underwater cameras, satellite imagery, or acoustic sensors. Deep learning models can then analyze this data to extract meaningful insights.

- **Species Identification**: Deep learning models can be trained to accurately identify different marine species, including endangered or rare ones. This can assist researchers in understanding biodiversity and ecosystem health.

- **Real-time Monitoring**: Implementation of real-time monitoring systems can provide timely information about the presence and activities of marine animals. This is crucial for addressing conservation challenges promptly.

- **Reduced Human Effort:** Automation of the detection and recognition process can reduce the need for manual labor in monitoring marine ecosystems. This allows researchers and conservationists to focus on more complex tasks, such as data interpretation and policy development.

- **Integration with Existing Technologies**: The outcomes of the project may involve integration with existing marine observation technologies, creating a more comprehensive and interconnected system for monitoring and managing marine environments.

- **Open-Source Tools and Datasets**: The project might contribute to the development of open-source tools, frameworks, or datasets that can be used by the broader scientific community, promoting collaboration and accelerating progress in the field.

It's essential to note that the specific outcomes will depend on the goals and scope of the project, the quality of data utilized in training of deep learning models, and the effectiveness of the chosen algorithms. For the latest information on this specific project, you may want to check recent publications, conference proceedings, or the project's official documentation.

# CHAPTER-9

# RESULTS AND DISCUSSIONS

## 9.1 MODULES

### 9.1.1 System

- Create Dataset:

  The dataset, which comprises images of marine animals to be classified, is divided into training and testing sets, with the testing set accounting for 30-20%.Pre-processing:

Resizing and reshaping the images into appropriate format to train our model.

- Training:

Use the pre-processed training dataset is used to train our model.

- Classification:

The results of our model is display of images are with one of the given input images.

### 9.1.2. User

- User registration

User can register with the mentioned details like name, email, password, confirm password, contact number.

- User login

In this page user can login with the email and password for further process

- Upload Image

The user has to upload an image, which needs to be classified.

- View Results

User views the classified image results.

- Logout

After complete the process user can logout from the process

## 9.2 Results

**Result page:** Here predicted output will see the user

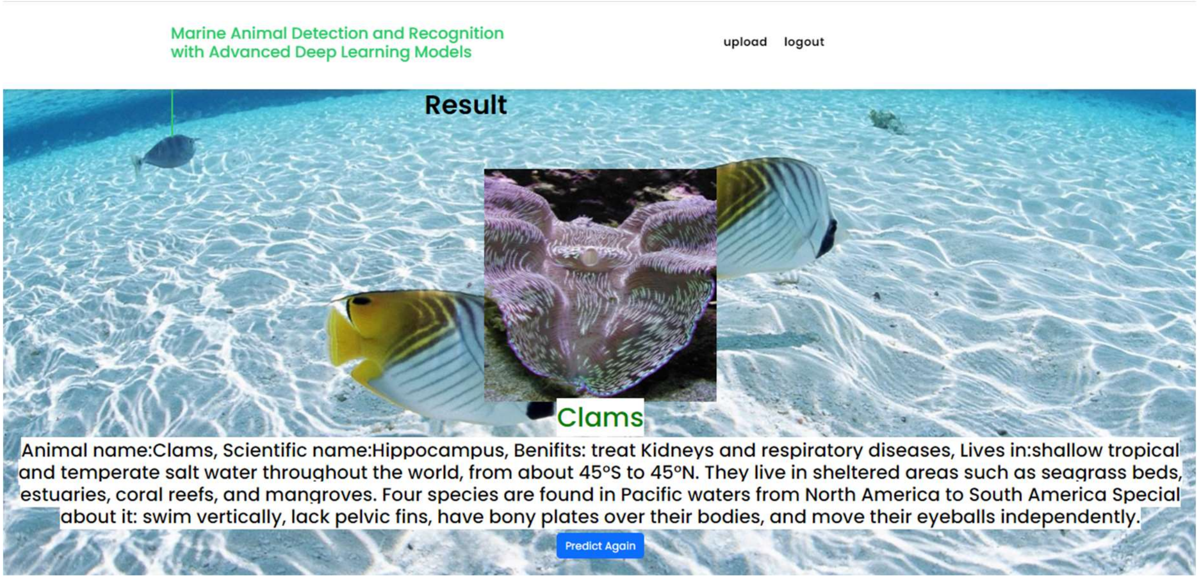


**Figure 9.1.Result1**

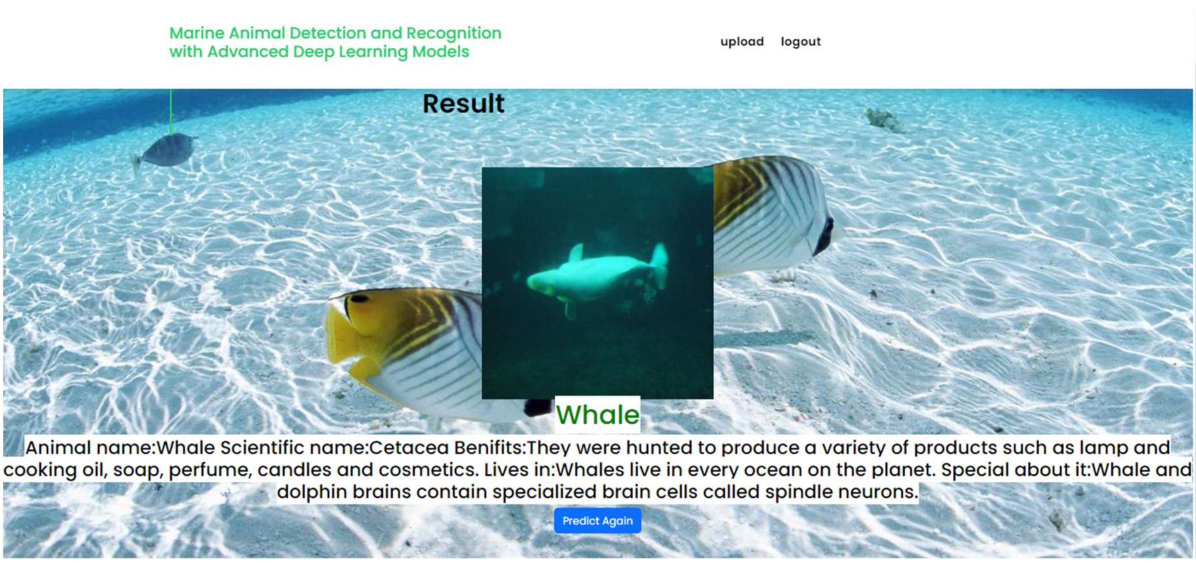


**Figure 9.2.Result2**

# CHAPTER-10

# CONCLUSION

In conclusion, the Detection and Recognition of Marine Animals project, employing high level deep learning models, represents a notable advancement in our efforts to understand and conserve marine ecosystems. Through the integration of cutting-edge technology, this project not only showcases the potential of artificial intelligence in ecological studies but also addresses critical challenges in marine biology and conservation. The precision achieved in monitoring, enabled by advanced deep learning models, provides reliable data on the presence, distribution, and behavior of diverse marine species. This accuracy is instrumental in directing targeted conservation strategies and preserving biodiversity in delicate marine ecosystems. Beyond its scientific contributions, the project serves as an educational tool, raising awareness about the importance of marine conservation.

The visualization of marine life and ecosystems captured by the system has the potential to engage and educate the public about the beauty and fragility of our oceans. Moreover, the interdisciplinary collaboration between computer scientists, marine biologists, and technological expertise with ecological insights. The project's ethical considerations and adherence to guidelines ensure that the technology aligns with ecological goals and minimizes potential negative impacts. As a continuous and iterative endeavor, the project allows for ongoing improvement, data collection, and model refinement, ensuring its adaptability to the evolving dynamics of marine ecosystems. In essence, the Marine Animal Detection and Recognition project signifies not only technological innovation but also a pivotal contribution to positive environmental change, reshaping how we perceive, study, and conserve the intricate web of life beneath the ocean's surface.

The " Detection and recognition of marine animals using sophisticated deep learning models" project stands as a significant leap forward in leveraging technology for the betterment of our oceans. It sets the stage for continued research and development, encouraging a more comprehensive understanding of marine ecosystems and aiding in the conservation and sustainable management of our seas. As we continue to refine these technologies, there's a tremendous opportunity to make a lasting and positive impact on the world's oceans and the diverse life they support.

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# APPENDIX-A

# PSUEDOCODE

```
# Import necessary libraries
# Function to load pre-trained model
def load_pretrained_model(model_path):
    model = load_model(model_path)
    return model
# Function to perform marine animal recognition
def marine_animal_recognition(model, image_path, classes):
    try:
        # Load and preprocess the image
        img = image.load_img(image_path, target_size=(224, 224))
        img = image.img_to_array(img)
        img /= 255
        img = np.expand_dims(img, axis=0)

        # Make predictions using the loaded model
        result = model.predict(img)
        predicted_class_index = np.argmax(result)
        predicted_class = classes[predicted_class_index]

        # Provide information based on the recognized class
        if predicted_class == 'Clams':
            msg = '''Animal name: Clams,
                    Scientific name: Hippocampus,
                    Benefits: treat Kidneys and respiratory diseases,
                    Lives in: shallow tropical and temperate salt water throughout the world, from
about 45°S to 45°N. They live in sheltered areas such as seagrass beds, estuaries, coral reefs,
and mangroves. Four species are found in Pacific waters from North America to South
America
                    Special about it: swim vertically, lack pelvic fins, have bony plates over their
bodies, and move their eyeballs independently.'''
        elif predicted_class == 'Corals':
```

```
        # Similar information for other classes
        msg = '''Animal name: Corals.
            Scientific name: Anthozoa.
            Benefits: help improve blood circulation and reduce inflammation, which can help alleviate pain and promote healing.
            Lives in: throughout the world's oceans, in both shallow and deep water.
            Special about it: sea animals that stay in one place throughout their adult lives.'''
    elif predicted_class == 'Crabs':
        # Similar information for other classes
        msg = '''Animal name: Crabs.
            Scientific name: Brachyura.
            Benefits: The omega-3 fatty acids in crab provide many benefits related to heart health.
            Lives in: all oceans and in fresh water. Some crabs live on land.
            Special about it: Crabs walk and swim sideways. Crabs eat both meat and plants, making them omnivores.'''
    elif predicted_class == 'Dolphin':
        # Similar information for other classes
        msg = '''Animal name: Dolphin
            Scientific name: Delphinus
            Benefits: keeping their environment in balance.
            Lives in: the ocean or brackish waters along coastlines.
            Special about it: grace, intelligence, playfulness, and friendliness to humans.'''
    elif predicted_class == 'Eel':
        # Similar information for other classes
        msg = '''Animal name: Eel
            Scientific name: Anguilliformes
            Benefits: replenish damage, reduce leprosy, strengthen tendons and bones
            Lives in: both freshwater and saltwater, with the majority of species found at sea.
            Special about it: Eels are characterized by their elongated, wormlike bodies.'''
    else:
        msg = 'Unable to recognize the marine animal.'

    return msg
```

```
    except Exception as e:
        return f"Error: {str(e)}"

# Example usage
model_path = 'path/to/your/model.h5'
loaded_model = load_pretrained_model(model_path)
image_path = 'path/to/your/marine_animal_image.jpg'
classes = ['Clams', 'Corals', 'Crabs', 'Dolphin', 'Eel']  # Adjust based on your actual classes
result_message = marine_animal_recognition(loaded_model, image_path, classes)

# Print the result message
print(result_message)
```

# APPENDIX-B

# SCREENSHOTS

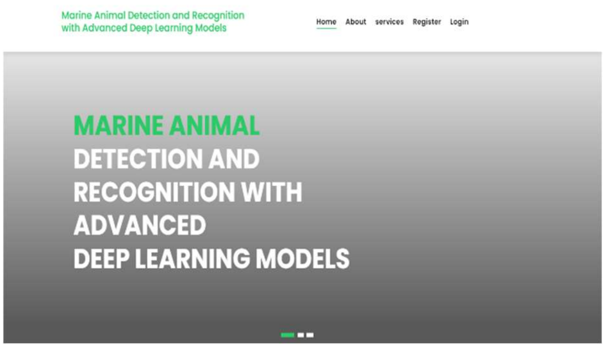



**Figure 11.1.HomePage**

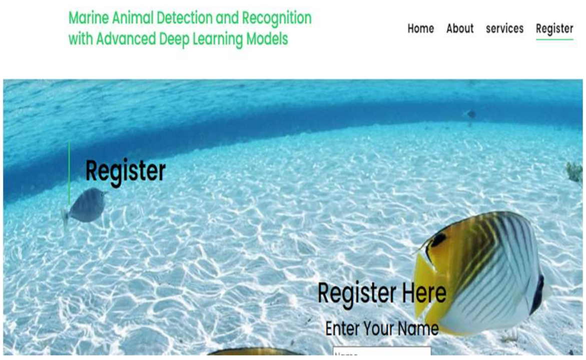



**Figure 11.2.RegisterPage**

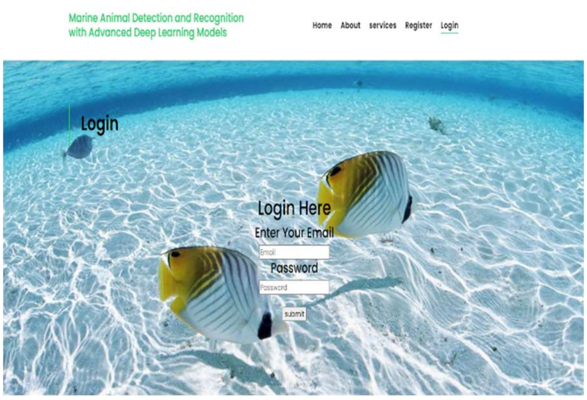



**Figure 11.3.LoginPage**

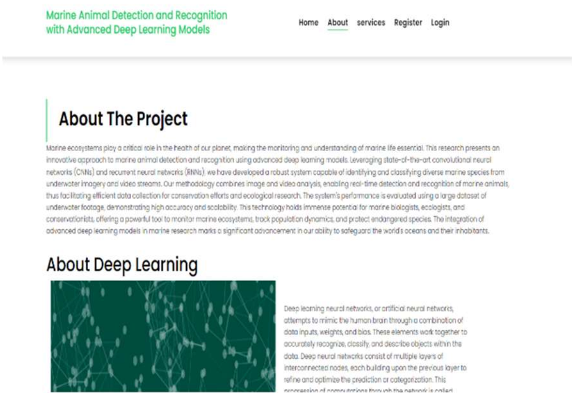



**Figure 11.4.AboutPage**

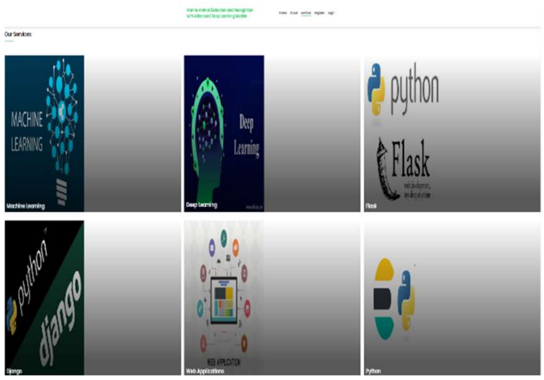



**Figure 11.5.InfoPage**

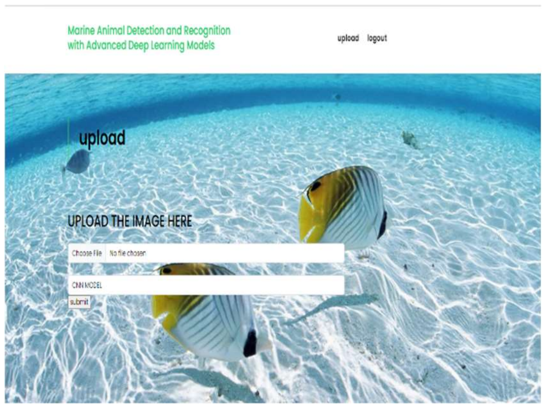



**Figure 11.6.UploadPage**

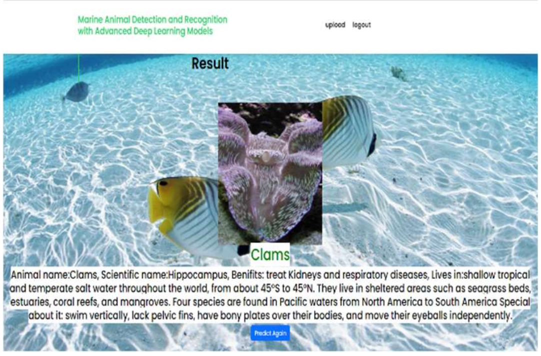
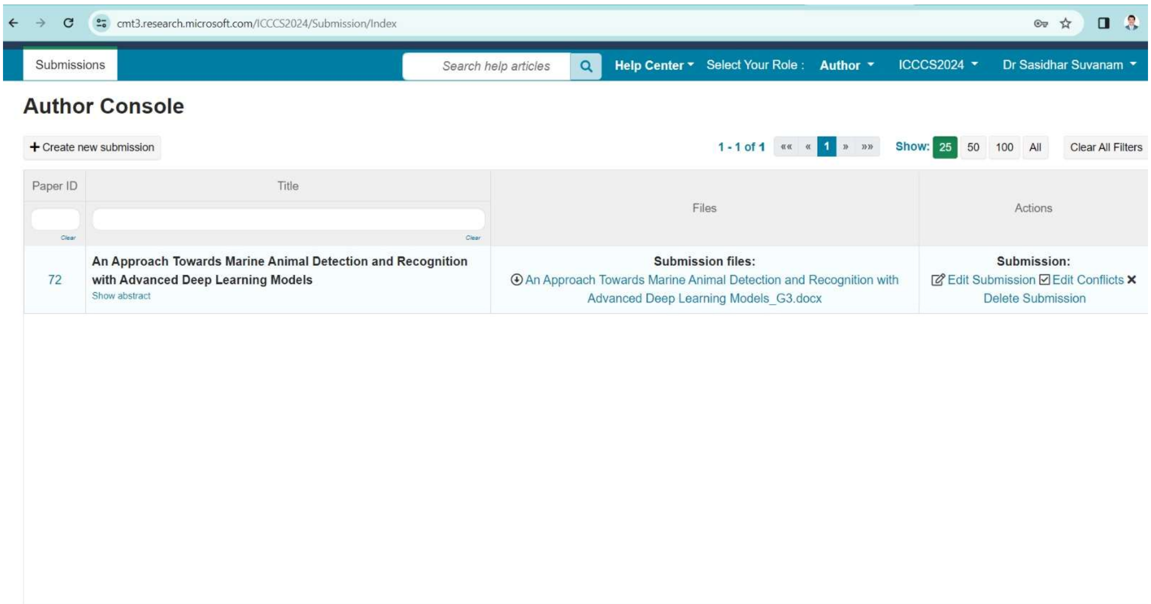
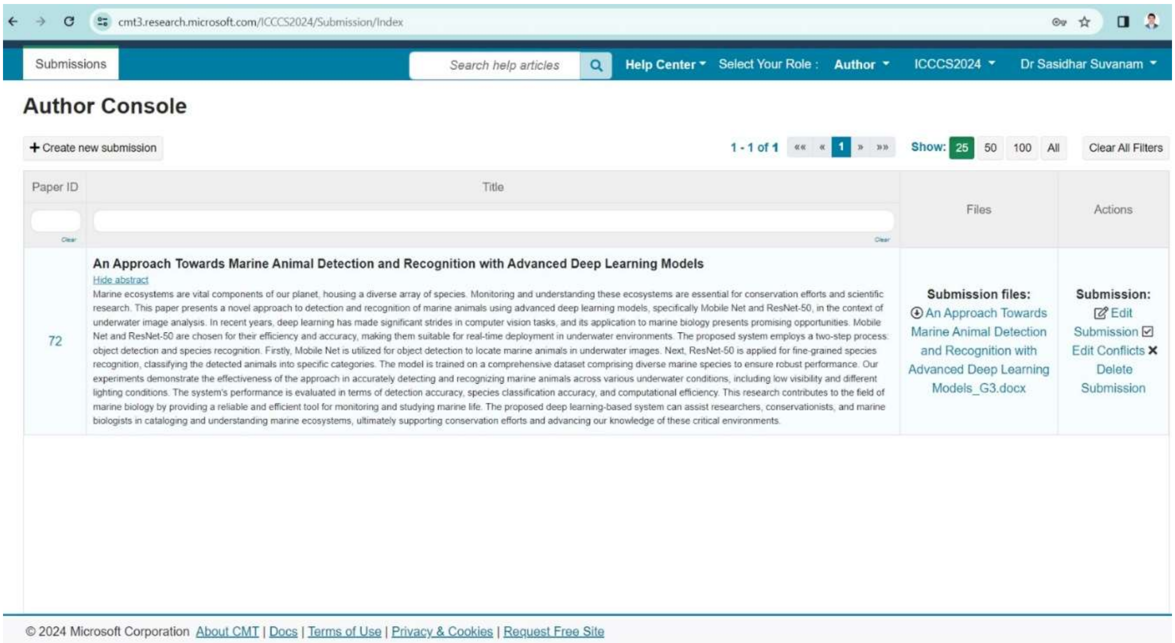



**Figure 11.7.ResultPage**

# APPENDIX-C
# ENCLOSURES

1. **Submitted the paper to IEEE International Conference on Communications and Computer Science (ICCCS2024) @ BMSCE, 22nd-24th May 2024.**



## 3. Similarity Index / Plagiarism Check report clearly showing the Percentage (%) – Attached.