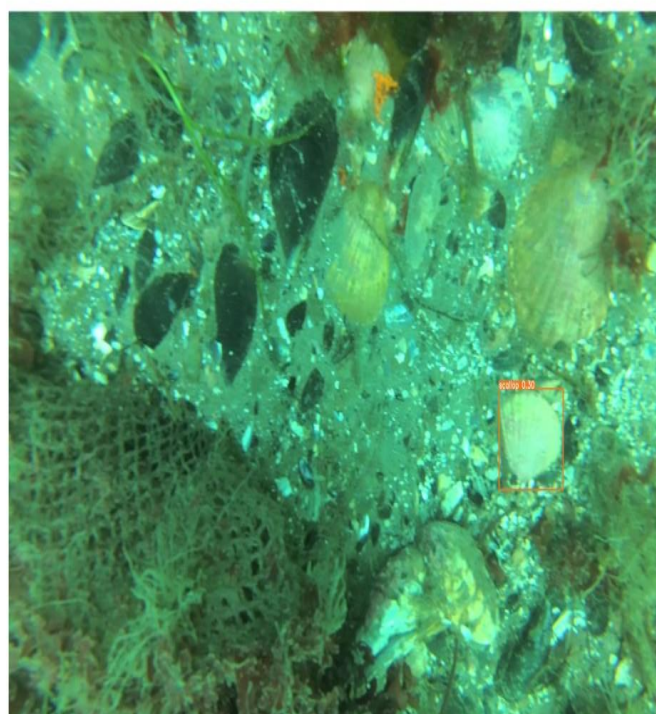
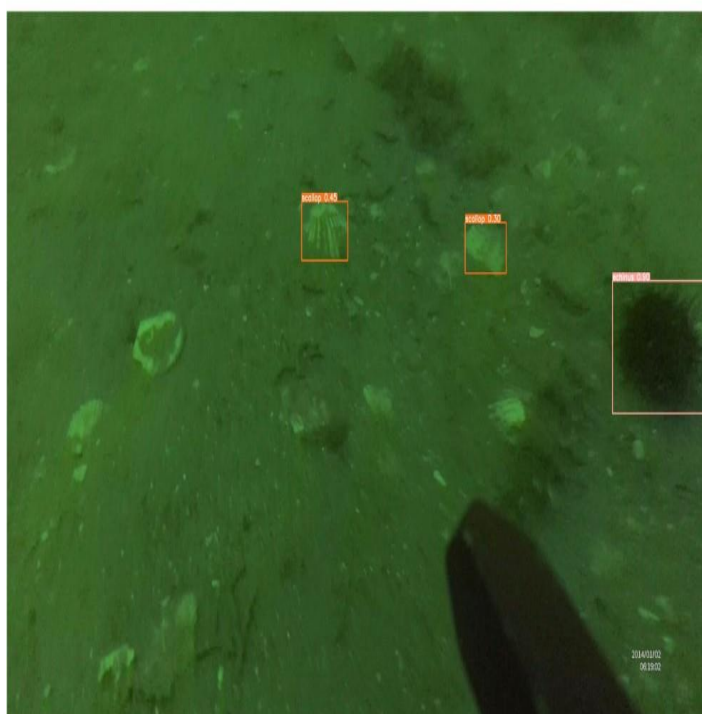
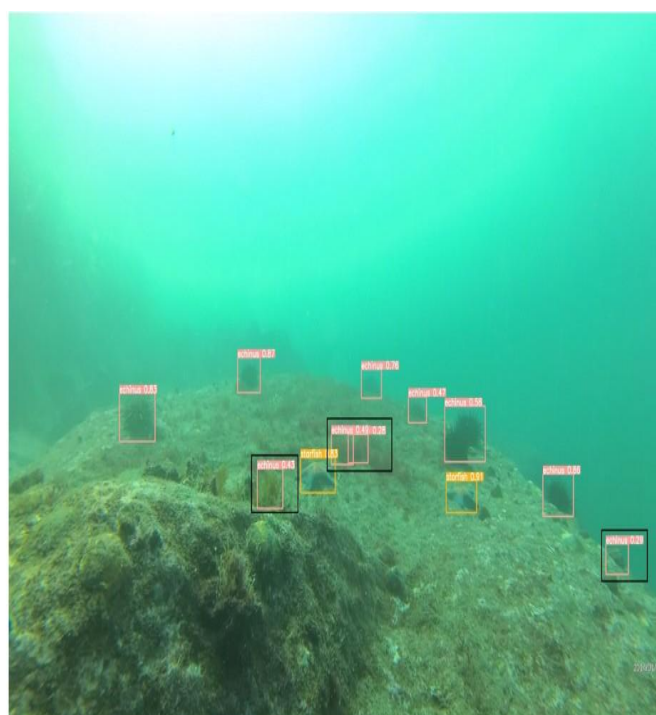
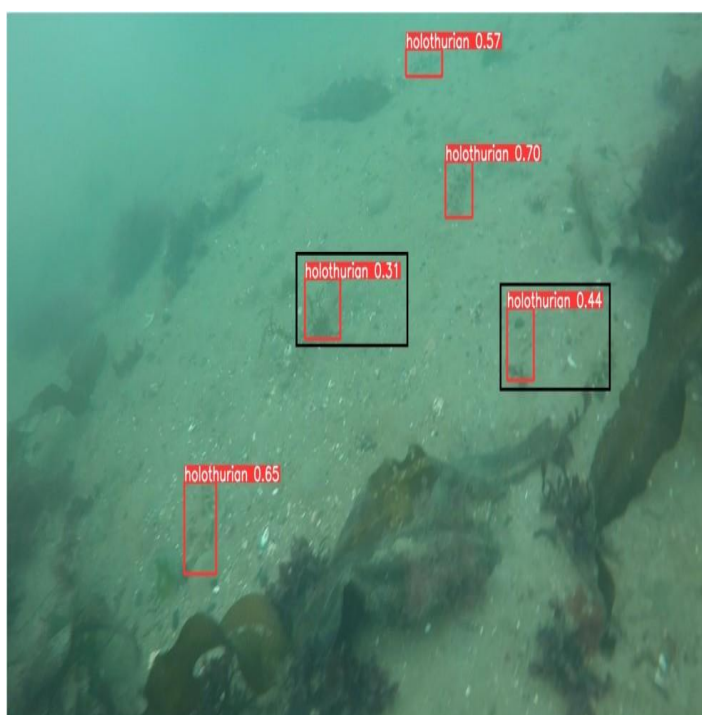


PROJECT SYNOPSIS

DEPARTMENT	ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING			
TITLE OF THE PROJECT	Real Time Recognition Of Underwater Images Using Deep Learning Techniques			
STUDENT NAMES/ USN/ PHONE/ MAIL ID	NAME	USN	PHONE	EMAIL-ID
	AYUSH ADITYA	1DS20AI015	8271301722	ayushaditya2949@gmail.com
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PROJECT TIMELINE (Tentative Start date- End Date)	April 2023 to January 2024			
PROJECT GUIDE	Prof. Ramya (Assistant professor DSCE)			
FIELD OF PROJECT	Machine Learning and Deep Learning			

PROJECT INTRODUCTION	<p>Artificial neural networks (ANNs) are a type of machine learning algorithm inspired by the structure and function of biological neurons. ANNs have been successfully applied to a wide range of applications, including image recognition, speech recognition, and natural language processing. One particular area where ANNs have shown promise is in the field of image recognition for underwater images. Underwater images present unique challenges due to factors such as poor visibility , color distortion, and occlusion. ANNs can help overcome these challenges by learning to recognize patterns and features in the images that are relevantfor classification. By evaluating the performance of ANNs on underwater image datasets, wehope to provide insights into the strengths and limitations of these technologies for this application. This could lead to the development of more accurate and efficient image recognition systems for underwater environments, which would have important implications for fields such as marine biology.</p> <p>Here are 5 key points to consider when applying artificial neural network technology to image recognition for underwater images:</p> <ol style="list-style-type: none">1. Pre-processing: Pre-processing techniques such as color correction, image enhancement, and noise reduction can improve the quality of the underwater images and increase the accuracy of the neural network's predictions.2. Data augmentation: Due to the limited availability of underwater image datasets, data augmentation techniques such as flipping, rotation, and scaling can be used to generate additional training data and improve the generalization of the neural network.3. Network architecture: The choice of neural network architecture depends on the specific task and the available computational resources. Convolutional neural networks (CNNs) are commonly used for image recognition tasks due to their ability to extract features from images.4. Training: Training the neural network requires a large amount of data and computational resources.5. Evaluation: The performance of the neural network can be evaluated using metrics such as accuracy, precision, recall, and F1 score. Cross-validation techniques can also be used to assess the generalization of the network to new data.
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Literature Survey Summary	<ul style="list-style-type: none"> • The study focuses on identifying the current state-of-the-art techniques and challenges in the field of artificial neural network technology and underwater image recognition. • Convolutional neural networks (CNN) are the most commonly used deep learning architecture for image recognition of underwater images. • The lack of standardized datasets, limited computational resources, and the need for better pre-processing techniques for underwater images are some of the challenges in this field. • Transfer learning, data augmentation, and hybrid models are suggested as potential methods to improve the accuracy of image recognition for underwater images. • Artificial neural network technology has the potential to improve the accuracy of image recognition for underwater images, with practical applications in various fields such as marine biology, underwater archaeology, and oceanography. • Other studies in this field may have used different deep learning architectures or techniques for image recognition of underwater images, such as recurrent neural networks or transfer learning from pre-trained models.

OBJECTIVES OF THE PROJECT	<ul style="list-style-type: none">• To develop a neural network-based system for accurately detecting and classifying human bodies in underwater images.• To explore and compare different neural network architectures and optimization techniques to improve the accuracy of human body detection.• To pre-process the images to remove noise and distortion and enhance the features relevant to human body detection in underwater images.• To evaluate the performance of the developed neural network system on a test dataset and compare it with existing methods.• To identify the limitations of the developed system and suggest areas for future improvements, such as exploring the use of other types of sensors or data sources to enhance human body detection in underwater environments.• To demonstrate the potential applications of the developed system, such as in search and rescue operations or marine biology research.• These objectives can guide the development and implementation of the project, and help to ensure that the project achieves its intended goals.

PROPOSED SOLUTION	<p>The proposed solution consists of several key components, including:</p> <ul style="list-style-type: none">• Data collection: Collecting a dataset of underwater images containing human bodies, which can be used for training and testing the neural network model.• Data pre-processing: Pre-processing the images to remove noise and distortion, and enhance the features relevant to human body detection in underwater images. This can include techniques such as contrast enhancement, edge detection, and image filtering.• Neural network architecture design: Designing a suitable neural network architecture for the human body detection task, which can include convolutional neural networks (CNNs) or recurrent neural networks (RNNs) with suitable hyperparameters.• Model training: Training the neural network model on the pre-processed dataset, using suitable optimization techniques such as stochastic gradient descent (SGD) or Adam optimizer.• Model evaluation: Evaluating the performance of the trained model on a separate test dataset, using appropriate metrics such as precision, recall, and F1 score.• Model refinement: Refining the model based on the evaluation results, by tuning hyperparameters or adjusting the network architecture.• Deployment: Deploying the trained model in a real-world underwater environment, using specialized hardware and communication systems.
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Tools Required	<ul style="list-style-type: none"> • Programming languages: Python or MATLAB can be used for implementing the neural network model and pre-processing the image data. • Deep learning frameworks: TensorFlow, Keras, or PyTorch can be used for building and training the neural network model. • Image processing libraries: OpenCV or scikit-image can be used for pre-processing the image data, such as filtering, segmentation, and feature extraction. • Data visualization tools: Matplotlib or seaborn can be used for visualizing the image data and the performance of the neural network model. • GPU computing: The use of a GPU can significantly speed up the training and testing of the neural network model. • Cloud computing platforms: Cloud computing platforms such as Amazon Web Services (AWS) or Google Cloud Platform (GCP) can be used for scalable and cost-effective deployment of the trained model. • Underwater cameras: Specialized underwater cameras can be used for capturing the image data in underwater environments. • Diving equipment: Diving equipment such as wetsuits, fins, and masks can be required for collecting image data in underwater environments.

Dataset Details Performance Metrics	<p>Dataset Details:</p> <p>The dataset can include a collection of underwater images containing human bodies, captured using specialized underwater cameras. The dataset can be divided into training, validation, and test sets, with appropriate labels for each image indicating the presence or absence of human bodies.</p> <p>Performance Metrics:</p> <ul style="list-style-type: none">• The performance of the developed neural network model can be evaluated using appropriate performance metrics, such as precision, recall, and F1 score. These metrics can be computed using the confusion matrix, which represents the number of true positives, false positives, true negatives, and false negatives.• Additional performance metrics that can be used to evaluate the model can include accuracy, area under the receiver operating characteristic curve (AUC-ROC), and mean average precision (mAP). These metrics can provide a comprehensive assessment of the model's ability to accurately detect and classify human bodies in underwater images.• The choice of performance metrics can depend on the project requirements and the intended application of the developed model. For instance, in search and rescue operations, a high recall rate (i.e., low false negative rate) can be more critical than high precision. <p>Therefore, the performance metrics can be selected based on the specific project goals and requirements.</p>
	Accuracy, Precision, Recall, F1Score
Demonstration Details including GUI	The project will be demonstrated via a web interface.

SYSTEM DIAGRAM	<pre>graph LR; A[Input Image] --> B[Image Pre-processing]; B --> C[Extract Features]; C --> D[Features Matching]; D --> E{Does object present in an image?}; E -- Yes --> F[Detect object]; E -- No --> G[Predict location];</pre>
ARE THERE AN STANDARD ^Y DATASETS AVAILABLE	1. https://www.kaggle.com/datasets/slavkoprytula/aquarium-data-cots 2. https://www.kaggle.com/datasets/utkarshsaxenadn/human-body-background-remover
Project Timeline	Feb 2023 – Feb 2024

Base Paper Link	<ol style="list-style-type: none"> 1. https://ieeexplore.ieee.org/document/9691259 2. file:///C:/Users/praveen/AppData/Local/Microsoft/Windows/INetCache/IE/0BTXQ6KJ/SE_1[1].pdf 3. file:///C:/Users/yash/AppData/Local/Microsoft/Windows/INetCache/IE/WIJNSH3W/10381-Article_Text-18493-1-10-20210808[1].pdf
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