SC-407 Project

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***Abstract*—Oceans constitute a vital component of Earth's ecosystem, playing a crucial role in regulating climate, supporting biodiversity, and sustaining livelihoods. However, increasing anthropogenic activities, including industrial waste discharge, plastic pollution, and oil spills, pose significant threats to ocean health and ecosystem integrity. Detecting ocean pollution is paramount for safeguarding marine environments, preserving marine biodiversity, and ensuring the sustainability of marine resources. Many systems in sciences and engineering can be modulated and simulated using different mathematical equations. In this project, we propose an image recognition-based approach for the detection of ocean pollution, leveraging advanced algorithms to analyse satellite or drone imagery. By identifying and quantifying pollutants such as plastic debris and non-plastic components like oil slicks and marine litter, our methodology aims to provide timely insights for environmental monitoring and management. Through the detection of ocean pollution, we strive to mitigate the adverse impacts of human activities on marine ecosystems, thereby promoting ocean conservation and sustainable development.**

***Index Terms*—Convolutional Neural network (CNN), Ocean Pollution Detection, Image Processing, Deep Learning, Plastic Waste Detection, Marine Ecology, Sustainable Development.**

I. Introduction

As marine ecosystems face escalating threats, the need to monitor and manage ocean pollution becomes increasingly evident. Pollution adversely impacts aquatic life, disrupts ecosystems, and jeopardises biodiversity, necessitating a proactive approach to identify and mitigate pollution sources for sustainable environmental conservation. The detection of ocean pollution is not only a matter of ecological significance but also holds implications for human health. Contaminated water poses risks through the consumption of polluted seafood and the compromise of drinking water quality.

A. Problem Statement

The objective is to provide an easy and cost-effective method using deep learning techniques that helps scientists and environmentalists predict measures for mitigating ocean pollution. Our goal is to tackle the problem of precisely identifying floating pollution targets in photos, which is an essential task for pollution management and environmental monitoring.

B. Relevant Works

Apart from sampling ocean depths and lab analysis, which requires skilled labour for the surveys, several studies have focused on detecting and monitoring pollutants in water bodies. One such algorithm introduced was the IER algorithm, inspired by the immune system, to accurately identify floating pollutants despite challenges like varying illumination and complex water patterns. Van Lieshout et al. (2020) developed an automated method using Faster R-CNN to detect plastic waste in rivers with a precision of 73%, aiding timely cleanup efforts. There have been efforts to fine-tune Faster R-CNN for sea-based plastic detection, achieving 96.5% accuracy, aiding in turtle preservation efforts.

C. Our Contributions

Our method combines image processing and neural network classification to accurately identify ocean pollutants like plastic and non-plastic wastes like oil spills and metals much faster than the existing solutions. Enhancing and reconstructing underwater images is a challenging task that has attracted significant attention in recent times. Because the cornea and water have the same refractive index, the eye loses around two-thirds of its refractive power when submerged, resulting in hazy vision. This approach represents a significant advancement in monitoring and mitigating ocean pollution, contributing significantly to environmental conservation efforts. Fine-tuning a convolutional neural network with curated datasets ensures superior pollutant classification and therefore contributes significantly to the ocean pollution detection problem.

D. Organisation

This paper introduces an image recognition-based method for detecting ocean pollution with lesser time complexity, highlighting the critical importance of environmental monitoring in marine ecosystems. It outlines a systematic integration of image processing techniques and convolutional neural networks (CNNs) to achieve highly accurate pollutant identification. While primarily focusing on CNNs, the method briefly explores avenues for enhancing accuracy. Results demonstrate the method's effectiveness in pollutant classification, underscoring its value in detecting ocean pollution and safeguarding marine environments.

II. Proposed Approach

Underwater images are not up to the mark, hence the preimage enhancement is very important. Among the significant pollutants, plastic is predominant, covering approximately 30% of the ocean surface. To address this, pre-image enhancement plays a vital role. Using the CNN Classifier, features are extracted from the images. The CNN classifier is trained on a dataset of 2560 images, categorized into three groups: plastic, metal, and other pollutants. The main blocks for detecting pollutes are input scanned image, pre-processing, feature extraction and CNN classifier. These blocks work together to effectively identify and classify pollutants present in underwater environments.

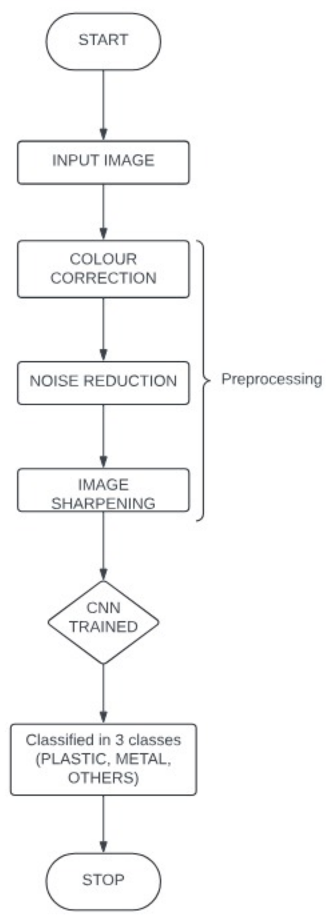

Fig. 1. Proposed approach to operate over the current problem

A. Image Pre-processing

1) Colour Correction: Underwater cameras often capture images with reduced quality due to low illumination in deep water areas, resulting in unclear visuals. To address this issue, we apply colour correction techniques. Colour correction employs a white balancing process to remove unwanted colour casts, restoring the original colour integrity of the images. This enhances the overall quality, making them clearer and easier to analyze.

2) Noise Reduction: Underwater images frequently suffer from noise, which can distort visual clarity. To mitigate this problem, we implement noise reduction techniques during preprocessing. These methods suppress unwanted noise in the images, resulting in cleaner and visually appealing outputs. By reducing noise, we enhance image quality, facilitating more accurate content analysis.

3) Sharpness Enhancement: To further enhance the quality and clarity of underwater images, we apply sharpness enhancement techniques. These methods improve the definition and crispness of edges and details in the images, making them sharper and visually striking. By enhancing sharpness, we highlight important features and elements, aiding in the identification and assessment of pollution elements such as plastic and metals.

B. Why CNN for the feature extraction?

We opted for a convolutional neural network (CNN) for feature extraction over other techniques like PNN (probabilistic neural network) and SVM (Support Vector Machine) due to several advantages. PNNs, while effective for classification tasks, can be memory intensive, especially when working with large datasets. Additionally, their performance can be sensitive to the chosen architecture and hyperparameters, requiring meticulous tuning. On the other hand, SVMs produce binary classification decisions and lack probabilistic outputs, limiting their interpretability compared to other methods. In contrast, CNNs automatically learn hierarchical representations of features from raw input data, making them highly suitable for tasks such as image recognition and classification. Their ability to capture spatial patterns and structures within images makes them a robust choice for feature extraction in visual data. Moreover, CNNs are scalable and adept at handling large datasets, which is crucial for real-world applications.

C. CNN Classifier

We proceed to train a convolutional neural network (CNN) classifier for categorizing the images into three distinct classes: plastic, metals, and other pollutants. A CNN classifier is specialized for image classification tasks, comprising convolutional, pooling, and fully connected layers.

Flatten Layer: This layer transforms the output from the preceding convolutional layers into a one-dimensional vector, facilitating processing by subsequent fully connected layers. It essentially converts the multi-dimensional output into a format compatible with dense layers.

Dense Layers: These layers are fully connected, where each neuron is linked to every neuron in the following layer. We incorporate two dense layers. The first dense layer has 128 units and uses the ReLU activation function. ReLU is commonly used in hidden layers because it helps the model learn complex patterns more quickly by preventing the vanishing gradient problem. This allows the model to converge faster during training.

The next dense layer has 3 units, representing the three categories we're classifying. It uses the softmax activation function, which is commonly used for tasks involving multiple classes. Softmax converts the raw scores into probabilities, making sure that when you add up all the probabilities for all the classes, it equals one. This allows the model to provide a probability distribution across all the classes, helping it make more accurate predictions.

D. Database

We have taken the dataset from the kaggle which has more than 2560 images. These images come in various resolutions, ranging from 640x480 to 1200x900 pixels. This diversity ensures that our dataset is representative and comprehensive for both training and testing our classifier. To standardise the input size for our classifier, we've converted all these images to a resolution of 224x224 pixels. Converting the images to a 224x224 resolution facilitates standardization, compatibility with pre-trained models, and efficient processing, ensuring optimal performance of our classifier on the Kaggle dataset.

III. ALGORITHMS

Algorithms should be numbered and include a short title. They are set off from the text with rules above and below the title and after the last line.

The first step that is required before training the model is properly modifying the dataset according to our requirements. The images(dataset) using which our model will be trained has to be preprocessed.

A. Converting a classifier from object

Deep learning neural networks are frequently used classifiers which require different layers and variable number of epochs. Less epoch means the model learns less about the given input but with too many epochs we face the problem of overfitting .Here we have used the Convolutional Neural Network which is basically a feed forward neural network. The common application of this is in image classification and pattern recognition problems.

TABLE I
PARAMATERS OF THE MODEL

Epoch	100
Convolutional Layers	3
Dense Neural Network Layers	2
Total classes	3

Convolutional Layers: We have used three convoluted layers in total. The first convolutional layer processes input images of size 224x224 pixels with 3 channels (RGB). It uses 6 filters of size 5x5 with ReLU activation, aiming to extract low-level features. The second convolutional layer employs 16 filters of the same size, also with ReLU activation, for deeper feature extraction. The third convolutional layer utilizes 64 filters of size 3x3 with ReLU activation to capture more complex features.

Max Pooling Layers : After each convolutional layer, a max-pooling layer with a pool size of 2x2 and stride of 2x2 reduces spatial dimensions and retains important features.

Flatten Layer: This layer converts the 3D feature maps outputted by the convolutional layers into a 1D feature vector, ready for input to the fully connected layers.

```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_15 (Conv2D)          (None, 224, 224, 6)       456

 max_pooling2d_15 (MaxPoolin  (None, 112, 112, 6)      0
 g2D)

 conv2d_16 (Conv2D)          (None, 112, 112, 16)      2416

 activation_5 (Activation)   (None, 112, 112, 16)      0

 max_pooling2d_16 (MaxPoolin  (None, 56, 56, 16)       0
 g2D)

 conv2d_17 (Conv2D)          (None, 54, 54, 64)        9280

 max_pooling2d_17 (MaxPoolin  (None, 27, 27, 64)       0
 g2D)

 flatten_5 (Flatten)         (None, 46656)             0

 dense_10 (Dense)            (None, 128)               5972096

 dropout_5 (Dropout)         (None, 128)               0

 dense_11 (Dense)            (None, 3)                 387

=================================================================
Total params: 5,984,635
Trainable params: 5,984,635
Non-trainable params: 0
_________________________________________________________________
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Fig. 2. Simulation results of the proposed approach.

Dense Layers : Two dense (fully connected) layers follow the flattened output. The first dense layer consists of 128 neurons with ReLU activation, aiming to learn high-level features. Dropout regularization with a rate of 0.5 is applied to mitigate overfitting by randomly setting a fraction of input units to zero during training.

Output Layer : The final dense layer consists of 3 neurons with softmax activation, producing probabilities for each class (assuming a classification task with 3 classes).

IV. DISCUSSION AND REMARKS

Our exploration of environmental monitoring and pollution detection reveals diverse approaches and considerations. We examined spectral imaging's potential for enhanced pollutant discrimination, balancing its benefits with challenges like cost, accuracy, and accessibility. Additionally, we stress the importance of balancing detection performance with computational efficiency and operational feasibility when deploying deep learning models like the Convolutional Neural Network (CNN). Our attempt to utilize contrast enhancement techniques to discriminate between images of plastic and ocean water revealed a challenge: the plastic features exhibited resonance with the texture present in the image. Consequently, this similarity hindered significant classification between the two entities. And thus chose not to employ the contrast technique in our proposed solution. On the other hand, techniques like colour correction, noise reduction using Gaussian blur and sharpening improved image processing to a great extent. Dataset diversity emerged as crucial for model training, with comprehensive datasets enhancing generalization and detection accuracy across various environmental conditions. To increase detection reliability, we provide the integration of several sensing modalities, for example, merging ambient sensor data with visual imaging. Our discussions highlight the complexity of pollutant detection tasks and underscore the need for interdisciplinary collaboration to drive innovation in environmental monitoring practices.

V. Numerical Results

Training and validation accuracy over epochs for a convolutional neural network (CNN) model had been done. This type of plot is commonly used to visualize how well the model is performing during training on the training data and generalizing to unseen data on the validation set. The below image shows the plot of training and validation accuracy over epochs.

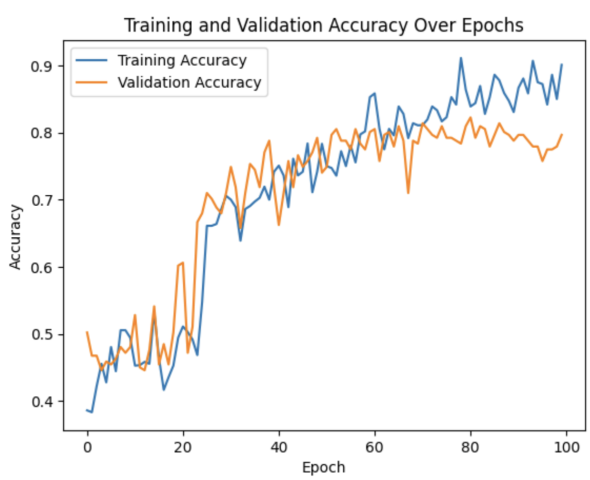

Fig. 3. Plotting epoch on the horizontal axis and accuracy after each epoch on the vertical axis.

The training and the validation accuracy are increasing steadily throughout the training process, which is a good sign. The performance of the classifier has been visualised in the form of a confusion matrix. It shows how many classifications were correct and incorrect. The image below shows the confusion matrix of the classifier.

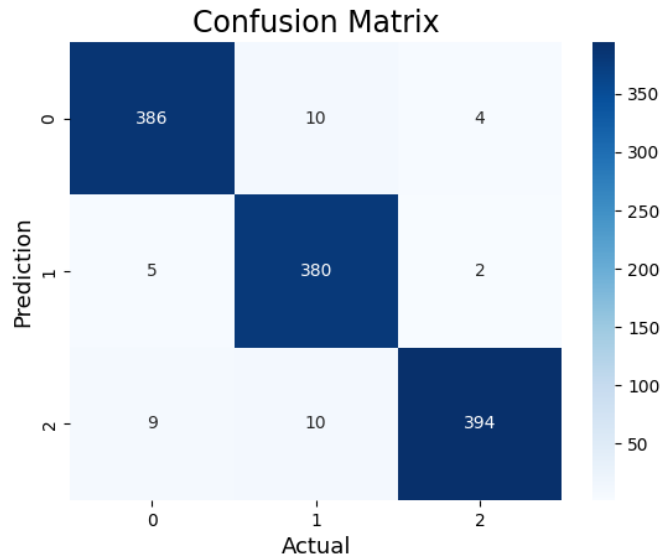

Fig. 4. Provides an experimental evaluation of our proposed methodology.

TABLE II
Results

Accuracy	96.67
Average Recall	96.66
Average Precision	97.01

From the matrix, we can see that the classifier can identify images correctly with the help of the diagonal value. The image preprocessing has increased the accuracy of the obtained output. The classification done with the help of the CNN model is also very accurate, as shown in the graph above. This will help researchers and conservationists determine the current pollution conditions. With this, they can determine the chances of survival of marine species in these adverse conditions.

VI. Conclusion

To conclude, our project focuses on the urgent requirement for early detection and control of ocean pollution to combat its negative effects on marine ecosystems and human well-being. We have created a practical and economical method for precisely recognising pollutants such as plastic and non-plastic waste in satellite or drone pictures by utilising cutting-edge image analysis and artificial intelligence algorithms. Our approach provides prompt data for environmental surveillance and control, intending to lessen the impact of human actions on marine habitats. Through teamwork across various fields and imaginative technologies, we anticipate a future where successful pollution identification results in improved oceanic conditions.