Pattern Recognition Algorithm To Identify Marine Animal Using Yolo Algorithm

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Abstract- *You Only Look Once (YOLO) is an algorithm which scans the image only once and as the name derives You look only once. YOLO works by dividing an image into a grid of cells and identifying the presence and position of objects with the given input image. The YOLO algorithm employs Convolutional Neural Networks (CNN) to descry objects in real-time. By using this algorithm, the marine species is identified in this paper. In this paper another Convolutional Neural Networks (CNN) algorithm Mobile Net and Single Shot Detector (SSD) were also used to perform comparative analysis. The Earth surface consists of water about 71 percent in that ocean holds about 96.5 percent of all Earth's water. Marine species which has ocean as habitat plays a vital part in maintaining the health and productivity of marine ecosystems. They contribute to nutrient cycling, give food and other resources for humans and other brutes, and help regulate the Earth's climate by absorbing carbon dioxide from the atmosphere. The 5 percent of ocean is only explored by the humans in that we knew only few species names. This paper is derived to identify the marine species in images or videos with name label using Deep learning (DL)object detection method. Object Detection is a system vision task that involves relating and localizing objects within an image or a videotape. One popular algorithm for object detection is You Only Look Once (YOLO), which is known for its speed and accuracy.*

Keywords- You Only Look Once (YOLO)Convolutional Neural Networks (CNN) Deep learning (DL) Single Shot Detector (SSD).

I. INTRODUCTION

This paper states different deep learning models for classification, identification and detection of Marine animals and other marine species. Deep Learning, and their algorithms are an area of Machine learning and Artificial Intelligence, has been used in a wide range of classifications and detections in recent years. Mainly, it is used in advanced level of image processing, voice recognition and natural language processing, image recognition and object detection fields. It performs literacy by creating at different situations representations for each image. Unlike other machine learning styles, there's no need of an expert for point birth on the images. convolution Neural Network(CNN), which is the introductory structure of deep learning models, consists of different layers. Deep learning models are designed using different computation of these layers. MobileNetV3 and SSD are also some of the algorithms comes under CNN they are used to do comparative analysis in this process. Instead, the marine animals were recognized by object detection method by using theCNN, YOLO algorithmsand implemented using Python OpenCV library which supports machine learning models. This identification, recognition and detection were performed with the help of webcam, videos or images. Animal Discovery Using Deep Learning Algorithm, the primary ambition is to allow the computers learn automatically without mortal intervention or assist and adapt behavior consequently[9].

Low-altitude small-sized object detection using lightweight feature-enhanced convolutional neural network which proposes about a lightweight feature-enhanced CNN able to perform detection with high precision detection for low-attitude flying objects in real time to provide guidance information to suppress black-flying UAVs [2]. Classification of Animals with Different Deep Learning Models derives that it performs learning by creating at different levels representations for each image. Unlike other machine learning methods CNN, which is the basic architecture of deep learning models, consists of different layers [4].

This paper presents the SSD algorithm, which is another popular object detection algorithm. The paper explains the technical details of SSD and compares it with other object detection algorithms, including YOLO [11]. The traditional homemade observation and detector- grounded automatic finding systems, this paper proposes a Sea Cucumber finding, position and analysis approach of actions pathway grounded on Faster R- CNN for ocean cucumbers under the deep learning framework [1].Marine Organism Detection and Classification from Underwater vision based on the Deep CNN Method says about Real-time object recognition is the key technology of the fishing robot, and the underwater environment is complex and changeable, which brings many difficulties to real-timeobject recognition [10].

In this paper two methods are compared You Only Look Once (YOLO) and Mobile Net, Single Shot Detector (SSD). The second section gives the literature review followed by the theory of the method. The fourth section gives simulation environment, experimental results, and performance metrics. The fifth section proceeds with the conclusion followed by the future enhancement.

II. RELATED WORK

Juan Li et al., **[1]** has proposed the traditional manual observation and sensor-based automatic detection methods, this paper proposes a Sea Cucumber detection, location and analysis approach of behavior trajectory based on Faster R-CNN for sea cucumbers using the multiple deep learning framework.

Ye Tao et al., **[2]** Low-altitude small-sized object detection using lightweight feature-enhanced convolutional neural network which proposes about a lightweight feature-enhanced CNN able to perform detection with high precision detection for low-attitude flying objects in real time to provide guidance information to suppress black-flying UAVs.

Benjamin J. Williamson et al., **[3]** Multisensory Acoustic Tracking of Fish and Seabird Behavior Around Tidal Turbine Structures in Scotland significant. This potentially represents a new mortality factor, which could significantly affect the population dynamics of many mobile marine species if significant proportions of the population are found to collide with devices.

OzkanInika et al., **[4]** Classification of Animals with Different Deep Learning Models derives that it performs learning by creating at different levels representations for each image. Unlike other machine learning methods CNN, which is the basic architecture of deep learning models, consists of different layers.

Michael A. Ainslie et al., **[5]** A Terminology Standard for Underwater Acoustics and the Benefits of International Standardization which says about increasing societal concern about possible detrimental effects of underwater noise on aquatic animals has led national and international regulators to require monitoring of underwater noise, with a consequent need for interdisciplinary harmonization of terminology.

E. Bhuvaneswari et al., **[6]** The Study and Analysis of Classification Algorithm for Animal Kingdom Dataset In this paper the dataset is trained and tested using remove percentage filter. Partitioned data set are evaluated individually using weka algorithms and the results are compared using error rate and accuracy rate.

Sachin Umesh Sharma et al., **[7]** A Practical Animal Detection and Collision Avoidance System Using Computer Vision Technique. In this paper, a simple and a low-cost approach for automatic animal detection on highways for preventing animal-vehicle collision using computer vision techniques are proposed.

Yuanyuan Huet al., **[8]** Object Detection of UAV for Anti-UAV Based on improved YOLOV3 improves it to detect UAV more precisely and it's the first time to introduce YOLO v3 based algorithm to UAV object detection for anti-UAV.

N. Banupriya et al., **[9]** Animal Detection Using Deep Learning Algorithm, The primary aim is to allow the computers learn automatically without human intervention or assistance and adjust actions accordingly.

Fenglei Han et al., **[10]**Marine Organism Detection and Classification from Underwater vision based on the Deep CNN Method says about Real-time object recognition is the key technology of the fishing robot, and the underwater environment is complex and changeable, which brings many difficulties to real-time object recognition.

III. THEORY

The Existing System is an end-to-end lightweight detection network architecture based on a fusion of Multiscale features for the detection of small objects flying at low attitudes, called LSL-Net, based on YOLO-tiny. The ADM specially identifies a scale for accurate detection of small objects in particular after the feature is extracted by the lightweight network block (LNB). The model, composed of these simple but effective modules, balances detection speed and accuracy well, and our experimental results demonstrate its excellent performance on the task of detecting low-altitude objects.

By taking the existing System as base methodology the proposed system is used to resolve the problem that arose in identifying the marine species name and its type this helps people to get knowledge about deep water marine species and their names.

The proposed System majorly concentrated about the CNN algorithm YOLO for Classification,Identification, Pattern recognition and prediction. YOLO means You Only Look Once is a method / way to do object detection. It is the algorithm behind how the code is going to detect objects in the image, video. YOLO is a classical pattern-recognition algorithm based on darknet-53 CNN architecture, which is used to identify and recognize the patterns. For Object detection YOLO divides an input image into an S × S grid. Still, that grid cell is responsible for detecting the object, If the middle point of an object falls into a grid. Each grid cell prognosticates bounding boxes and confidence scores for those boxes. This means that the entire identification of marine species in image or video is done in a single algorithm run.The image or video input is taken by the algorithm in the initial process, then the image frame is undertaken by CNN and then the frame is divided into grids by YOLO and it identifies the pattern in frame as YOLO is a pattern recognition algorithm. Then this process is further moved to classification and feature extraction which helps to identify the exact species, this image is compared with the predefined dataset in YOLOv3 that is Image net dataset, then the bounding boxes and class probability and name label are deployed around the object. Finally, the marine species in the input image or video is identified using object detection methodologies.

A 1. Research Methodology

Identification of Marine Animals with images is quite easy if we have trained dataset, but identification with video or using Webcam in marine, or in aquarium is probably a difficult one. This project simplifies the task by using Deep learning Convolutional Neural Network (CNN)algorithm named You Only Look Once (YOLO) and this algorithm is implemented in this project using python language in jupyter notebook, the python Library OpenCV is used to access images or videos and then the video frame is segmented into grids next to it the pattern is recognized from the frame then it is classified and feature extracted and the input data is matched with Image net a predefined dataset or we can use our own custom data set, Once the pattern or the image matches it identifies the video or image gets bounding boxes with confidence score of thosemarine animals.

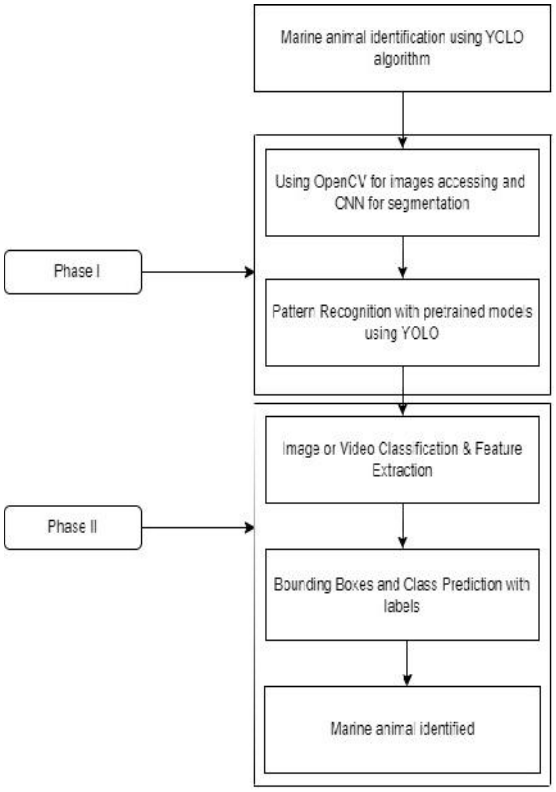

FIG 1. Research Methodology

A 2. Algorithm Implementation

The algorithm that was focused in this paper for identifying marine species with label and class probability was YOLO and the performance of YOLO v3 is compared with another CNN algorithm named Mobile Net-SSD. This comparative analysis mainly focuses the accuracy percent and the performance of the algorithm in the particular image or video capture. The detection is completed with the combination of Mobile net and SSD algorithms by combining these two only we can perform detection, but while using YOLO the detection can be performed with only using a single algorithm and also it splits the image or video frames into grids which provides high prediction accuracy than Mobile net and SSD.

YOLO v3

YOLO v3 is a state-of-the-art real-time object detection algorithm. It stands for "You Only Look Once" and is a neural network-based approach to object detection that divides an image into a grid of cells and applies a convolutional neural network to each cell to predict bounding boxes and class probabilities. YOLOv3 algorithm and has several features that make it particularly effective, including multi-scale prediction, YOLOv3 uses three different scales to predict bounding boxes and class probabilities, which helps it detect objects of different sizes.

Darknet-53 architecture: YOLOv3 uses a deep neural network architecture called Darknet-53, which is based on residual connections and has 53 layers.

Non-max suppression: YOLOv3 uses non-maximum suppression to eliminate overlapping bounding boxes and improve detection accuracy.

Convolutional layers: YOLO uses many convolutional layers to extract features from an input image. The output of a convolutional layer is calculated through:

Anchor boxes: YOLO uses anchor boxes to predict object bounding boxes. Each anchor box is defined by a width and height, and the network predicts offsets and scales for each anchor box. The predicted bounding box can be calculated as follows:

```
center_x = int(detection[0] * width)
center_y = int(detection[1] * height)
w = int(detection[2] * width)
h = int(detection[3] * height)
x = int(center_x - w / 2)
y = int(center_y - h / 2)
```

Non-maximum suppression:

YOLO uses non-maximum suppression to remove overlapping bounding boxes and improve detection accuracy. Hence YOLO is assumed to be a high accuracy object detection algorithm comparing Mobile Net and SSD.

IV. EXPERIMENTS AND RESULTS

The main Objective of this paper is to know the species of marine animal with name labels in videos of images for the purpose spreading awareness about different types and names of marine animals. The objective for using YOLO (You Only Look Once) for marine animal detection could be to accurately identify and locate different species of marine animals in real-time using computer vision, which helps to identify the marine species in the input image or video and knew the species name by its label displayed in the monitor. This can be useful for various applications, including marine research, conservation efforts, and even commercial fishing industries. The models are used to detect marine animals in images or video footage in real-time with high accuracy and speed. Additionally, the objective may also involve optimizing the YOLO model to detect and track marine animals under varying environmental conditions, such as low light, water clarity, and weather conditions, to ensure reliable detection performance in diverse scenarios.

A 1. Simulation Environment

Jupyter Notebook is an open- source web operation that allows people to produce and partake documents containing live codings, equations, visualizations, and narrative textbook. It supports a variety of programming languages, including Python, R, Julia, and more.One of the main benefits of using Jupyter Notebook is its interactive nature. Users can execute code cells in real-time and see the output immediately, making it an ideal tool for data analysis, experimentation, and collaboration. The notebook interface also allows for the creation of rich visualizations, such as plots and graphs, directly in the notebook.

Jupyter Notebook can generate different types of output, depending on the type of content you're working with. Some of the most common types of output in Jupyter Notebook include:

Images: Jupyter Notebook can display image files, such as JPEG or PNG files, within cells.

Plots and charts: Jupyter Notebook support many different plotting libraries, such as Matplotlib and Plotly, which can be used to generate charts, histograms, scatter plots, and other visualizations.

Audio and video: Jupyter Notebook can play audio and video files, such as MP3 or MP4 files, within cells.

Another key feature of Jupyter Notebook is its ability to support markdown language, which allows users to create formatted text and documentation within the same document as their code. This makes it easy to write explanatory text and include visual aids such as images and videos. Jupyter Notebook has become a popular tool in a variety of fields, including data science, scientific computing, education, and journalism. Its ease of use and flexibility make it a valuable tool for anyone who needs to analyze data or communicate code and results to others.

A 2. *Architecture diagram*

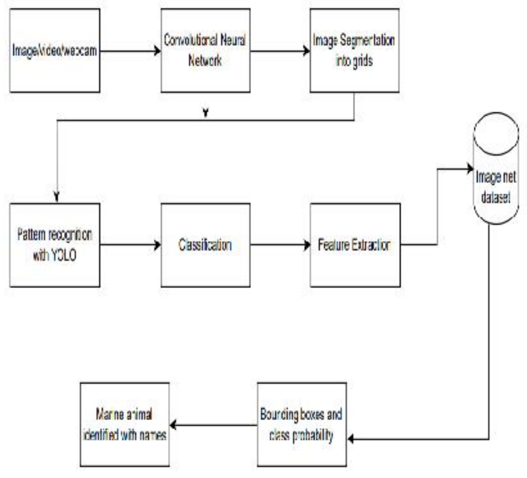

FIG 2. Architecture Diagram

These architecture is splitted into several modules they were implemented to obtain the output results those modules are

- Image acquisition
- Collecting data set and Segmentation
- Pattern recognition
- Feature Extraction & Classification
- Class Accuracy& Identification

Image acquisition

The Image or Video is captured using Webcam, or we can also import images from our own dataset or External sources. This process is done with the help of Python OpenCV library it helps to process image or video.

Collecting data set and Segmentation

The next step is to collect and store the image or video captured for this purpose we can use our CPU memory and the dataset collected can be custom dataset or pre trained dataset. The pre trained dataset would be trained already and will be ready for testing where-else, the custom dataset needs training. Then the input image is segmented using CNN algorithm into SxS grids and each grid are given importance for pattern recognition.

Pattern recognition

For pattern recognition we are applying YOLO algorithm. YOLO means You Only Look Once is a method / way to do object detection. It's the algorithm/ strategy behind how the law is going to descry objects in the image.YOLO is a classical pattern-recognition algorithm based on darknet-53 CNN architecture, which is used to identify and recognize the patterns.

Feature Extraction & Classification

The YOLO algorithm consists of a 24-layer convolutional neural network (CNN) for feature extraction, and two fully connected layers for predicting the probabilities and coordinates of objects this will help to extract the features in frames. YOLO algorithm based on classification they work in two stages. In the first step, we are opting from the image intriguing regions. Also we are classifying those regions using convolutional neural networks. This result could be veritably slow because we've to run vaticination for every named region.

Class Accuracy &Identification

The Classes are predicted according to their images and bounding boxes are created around the species with the class probability, and the names of the species are displayed in the images or videos. Identification is done by matching the datasets and applying name labels and the result will be display in the live Monitor or the in image uploaded by user

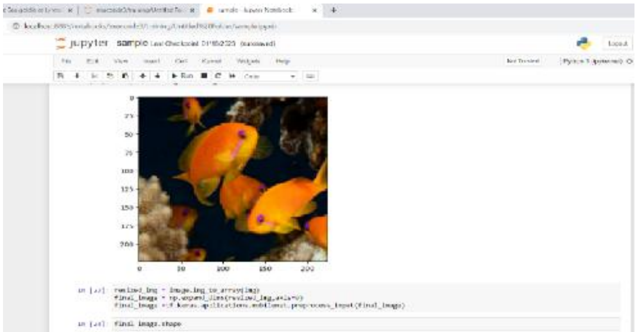

FIG .3 Image Acquisition

FIG 4. Class accuracy and Identification

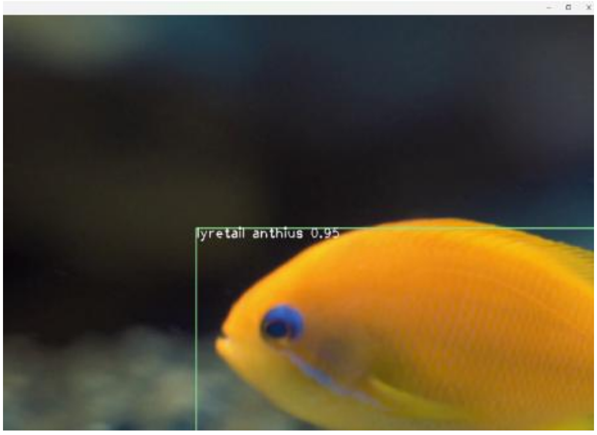

FIG 5. Identidication with accuracy in video file

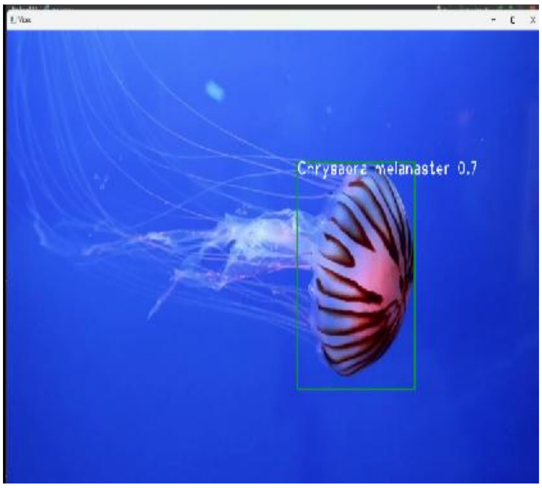

FIG 6. Identidication with accuracy in video file

FIG 7. Identidication with accuracy in video file

A 3. *Performance Metrics*

The performance of both the algorithm Mobile net , SSD and You Only Look Once (YOLO**)** is compared under this title. The performance of YOLO is consecutively high because YOLO is an object detection algorithm and it is also an classical pattern recognition algorithm which is effectively accurate in result as it segments the frame into SxS grids and therefore evaluates every single grid and then it finalizes the identification of marine species and name label. Where as Mobile net, Single Shot Detector (SSD) algorithm uses a multi-scale feature map to detect objects at different scales and aspect ratios which results in low accuracy than YOLO.

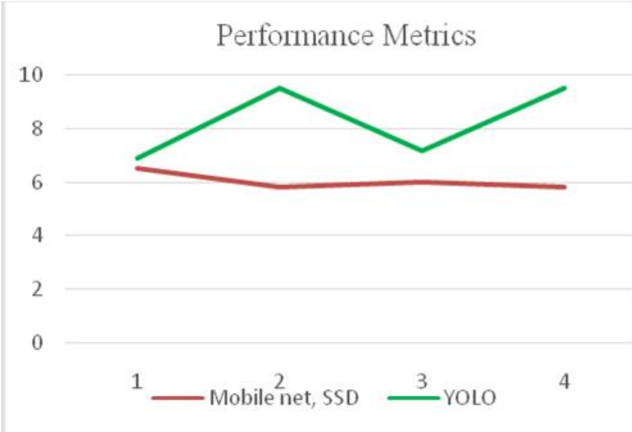

FIG 8. Performance evaluation of algorithms

V. DISCUSSION AND CONCLUSION

In this paper, we have discussed the concept of object detection and identification in a video using OpenCV in Python, using various methods. We have also discussed in detail, and performed a comparative analysis between the two famous object detection algorithms such as YOLO and Mobile net, SSD. The Mobile Net SSD combines these two models to perform object detection in real-time on mobile and embedded devices. This provides 70 percent accuracy.

YOLOv3 is a neural network-based approach to object detection that divides an image into a grid of cells and applies a convolutional neural network to each cell to predict bounding boxes and class probabilities. YOLOv3 is an improvement over previous versions of the YOLO algorithm and has several features that make it particularly effective, this provides a detection accuracy over 80 percent which is better than Mobile Net and SSD. This YOLO algorithm also provides class probability percent which is not provided by the Mobile net.

All our models could successfully detect all fishes from separating it from the background in the input image or video with 90 percent detection accuracy and in real-time detection speed.

VI. FUTURE SCOPE

YOLO is a real-time object detection algorithm that uses deep neural networks to detect objects in images and video streams. YOLOv3 builds upon the success of its predecessors, YOLO v1 and YOLO v2, and introduces several improvements that enhance its performance such as better accuracy, Faster inference, Support for multiple object classes, Improved training process, Support for custom models and YOLO represents a significant improvement over previous versions of the algorithm and is widely used in research and commercial applications for object detection. By this algorithm this paper is developed for marine animal identification in further enhancement this can also be implemented with other YOLO versions and this process can be developed with a user interface for user accessing as Webpage or Mobile Application. Other future enhancements like to improve the accuracy of the model is to train it on a more diverse set of images. This could involve collecting more images of different types of marine animals in various environments and lighting conditions. This helps to improve the process to the next stage as development requires.

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