Project Title

Performance Analysis of Conventional Neural Network Models for Detecting sMarine animals Under Varying Conditions

Details

1. Yolo
2. Mobilenet SSD
3. FRCNN

All three networks will be trained using the same dataset. Comparative analysis of these models will used to determine which model performed better for the given dataset and under varying deep-sea conditions.

Flow

1. Dataset and annotation
2. Train the three networks from scratch and transfer learning taking base models.
3. Test all six models on the under water marine life videos (considering different conditions includes lighting conditions and different species) for validation.
4. Calculate the performance of these models and plot.

Note (Modifications and changes can be included if required)

Literature Survey

1. **Comparative analysis on Deep Convolution Neural Network models using Pytorch and OpenCV DNN frameworks for identifying optimum fruit detection solution on RISC-V architecture [Link]**

   In this paper, four neural networks are trained on coco-dataset. Based on the inference results obtained from all the networks and f1-score, recall and mean scare error are calculated. All the testing is done on RISC-V platform and the model validation are done in real-time.

2. **Detection of Marine animals in a new underwater dataset with varying visibility [Link]**

   In this paper, three versions of yolo networks are trained and tested on marine dataset. Three versions of yolo networks are V5, V6 and V7. The models are tested on marine video. Yolo V5 outperformed both yolo V6 and yolo V7. A user interface is provided, where the user can feed in the input image for detecting the fishes.

3. **Deep neural networks for automated detection of marine mammal species [Link]**

   In this paper, a study of variety of deep neural networks to detect the vocalizations of endangered North Atlantic right whales (*Eubalaena glacialis*). A comparison of performance of these deep architectures to that of traditional detection algorithms for the primary vocalization produced by this species are done. Deep neural network trained with recordings from a single geographic region recorded over a span of days is capable of generalizing well to data from multiple years and across the species' range, and that the low false positives make the output of the algorithm amenable to quality control for verification is well demonstrated in this paper. The deep neural networks developed are relatively easy to implement with existing software, and may provide new insights applicable to the conservation of endangered species. LeNET and VGG networks are trained on DCLDE dataset.

4. Marine organism detection and classification from underwater vision based on the deep cnn method [Link]

In this paper, the underwater robot development is used to detect and locate the main target from underwater vision. This research is based on the deep convolutional neural network (CNN) to realize the target recognition from underwater vision. The RPN (Region Proposal Network) is used to optimize the feature extraction capability. Deep learning dataset is prepared using an underwater video obtained from a sea cucumber fishing ROV (Remote Operated Vehicle). The inspiration of the network structure and the improvements come from the Faster RCNN and Hypernet method, and for the underwater dataset, the method proposed in this paper shows a good performance of recall and object detection accuracy. The detection runs with a speed of 17 fps on a GPU, which is applicable to be used for real-time processing.

5. Automated fish detection in underwater videos by a deep neural network-based hybrid motion learning system [Link]

In this paper, an effective fish sampling techniques using underwater videos and image processing to automatically estimate and consequently monitor the fish biomass and assemblage in water bodies is developed. Such approaches should be robust against substantial variations in scenes due to poor luminosity, orientation of fish, seabed structures, movement of aquatic plants in the background and image diversity in the shape and texture among fish of different species. A unified approach to detect freely moving fish in unconstrained underwater environments using a Region-Based Convolutional Neural Network, a state-of-the-art machine learning technique used to solve generic object detection and localization problems is used. To train the neural network, a novel approach to utilize motion information of fish in videos via background subtraction and optical flow, and subsequently combine the outcomes with the raw image to generate fish-dependent candidate regions is considered. Two benchmark datasets extracted from a large Fish4Knowledge underwater video repository, Complex Scenes dataset and the LifeCLEF 2015 fish dataset to validate the effectiveness are used. A detection accuracy (F-Score) of 87.44% and 80.02%

respectively on these datasets, which advocate the utilization of our approach for fish detection task is obtained.

6. Underwater fish species recognition using deep learning techniques Link

In this paper, automated fish species identification using technology is trained and developed to help the marine science to evolve further. Image classification tasks have seen a rise with the introduction of deep learning techniques. This paper proposes a hybrid Convolutional Neural Network (CNN) framework that uses CNN for feature extraction and Support Vector Machine (SVM) and K-Nearest Neighbour (k-NN) for classification. Both the proposed frameworks are tested on Fish4Knowledge dataset. Experimental results show that the proposed framework gives better results than most of the traditional as well as existing deep learning techniques.

7. Underwater Fish Detection and Counting Using Mask Regional Convolutional Neural Network Link

In this paper, issues related to fish production to the development of fish farming, and encountered throughout the hatching process is the counting procedure is addressed. Previous research mainly depended on the use of non-machine learning-based and machine learning-based counting methods and so was unable to provide precise results. In this work, a robotic eye camera to capture shrimp photos on a shrimp farm to train the model is used. The image data were classified into three categories based on the density of shrimps: low density, medium density, and high density. The parameter calibration strategy to discover the appropriate parameters and provided an improved Mask Regional Convolutional Neural Network (Mask R-CNN) model is evaluated. As a result, the enhanced Mask R-CNN model can reach an accuracy rate of up to 97.48%.

8. Real-time marine animal detection using yolo-based deep learning networks in the coral reef ecosystem Link

In this paper, the advancement of marine resources and environment research, the ecological functions of reef-building coral reef ecosystems distributed in warm shallow waters of the ocean that are being continuously discovered and valued by people is taken as base. It is important for ecosystem protection to monitor the population of marine animals. Besides, many projects of Autonomous Underwater Vehicle (AUV) also need technology to perceive and understand environment information in real-time for better decision-making. Therefore, marine animal detection has become a challenge for researchers to study nowadays. Deep neural network models have been used to solve fish-related tasks and gained encouraging achievements, but there are still many problems in this field. In this paper, several YOLO-based methods are chosen for comparison. Experiment results indicate that these methods can recognize the marine animals in coral reef quickly and accurately. Finally, several recommendations for model improvement according to assessment results are presented.

9. **Methods studies for attached marine organisms detecting based on convolutional neural network Link**

In this paper, neural networks are used to detect marine targets which has been an important research direction in the field of target detection. Traditional detection models are generally only for fish, coral, large plants and animals and other easy to detect targets, for the attached marine species that are not easy to detect there are problems such as lower detection accuracy, slower speed, and large interference in the sea environment. With the increasing problems caused by the attachment of marine organisms, the identification methods for marine attached organisms are also receiving more and more attention. In this paper, the original YOLO v5 is improved in terms of activation function, optimized image information extraction method, and balanced positive and negative samples. Finally, an improved YOLO v5 target detection algorithm is proposed and tested on a self-built dataset. The experimental results show that the values of mAP and F1 of the improved YOLO v5 target detection algorithm are 72.1% and 0.722, respectively, which are better than other target detection algorithms in terms of accuracy and reliability.

10. Deep learning based deep-sea automatic image enhancement and animal species classification [Link]

In this paper, an image enhancement and classification pipeline that allows automated processing of images from benthic moving platforms is proposed. Deep-sea (870 m depth) fauna was targeted in footage taken by the crawler "Wally" (an Internet Operated Vehicle), within the Ocean Network Canada (ONC) area of Barkley Canyon (Vancouver, BC; Canada). The image enhancement process consists mainly of a convolutional residual network, capable of generating enhanced images from a set of raw images. The images generated by the trained convolutional residual network obtained high values in metrics for underwater imagery assessment such as UIQM (~ 2.585) and UCIQE (2.406). The highest SSIM and PSNR values were also obtained when compared to the original dataset. The entire process has shown good classification results on an independent test data set, with an accuracy value of 66.44% and an Area Under the ROC Curve (AUROC) value of 82.91%, which were subsequently improved to 79.44% and 88.64% for accuracy and AUROC respectively. These results obtained with the enhanced images are quite promising and superior to those obtained with the non-enhanced datasets, paving the strategy for the on-board real-time processing of crawler imaging, and outperforming those published in previous papers.

11. Underwater image classification algorithm based on convolutional neural network and optimized extreme learning machine [Link]

In this paper, target recognition in the complex underwater environment is carried out by filtering noise in the feature extraction stage of underwater images rich in noise, or with complex backgrounds, and improving the accuracy of target classification in the recognition process. This paper discusses on improving the accuracy of underwater target classification. This paper proposes an underwater target classification algorithm based on the improved flow direction algorithm (FDA) and search agent strategy, which can simultaneously optimize the weight parameters, bias parameters, and super parameters of the extreme learning machine (ELM). As a new underwater target classifier, it replaces the full connection layer in the traditional classification network to build a classification network. In the first stage of the network, the DenseNet201 network pre-trained by ImageNet is used to extract features and reduce dimensions of underwater images. In the second stage, the optimized ELM classifier is trained and predicted. In order to weaken the uncertainty caused by the random input weight and offset of the introduced ELM, the fuzzy logic, chaos initialization, and multi population strategy-based flow direction algorithm (FCMFDA) is used to adjust the input weight and offset of the ELM and optimize the super parameters with the search agent strategy at the same time. FCMFDA-ELM classifier on Fish4Knowledge and underwater robot professional competition 2018 (URPC 2018) datasets, and achieved 99.4% and 97.5% accuracy, respectively was tested. The experimental analysis shows that the FCMFDA-ELM underwater image classifier proposed in this paper has a greater improvement in classification accuracy, stronger stability, and faster convergence. Finally, it can be embedded in the recognition process of underwater targets to improve the recognition performance and efficiency.

12. An open-set framework for underwater image classification using autoencoders Link

In this paper, mainly intends to address the underwater image classification problem in an open-set scenario. Image classification algorithms have been mostly provided with a small set of species, while there exist lots of species not available to the algorithms or even unknown to ourselves. Thus, an open-set problem and extremely high false alarm rate in real scenarios, especially in the case of unseen species is used. Motivated by these challenges, the proposed scheme aims to prevent the unseen species from going to the classifier section. To this end, a new framework based on convolutional neural networks (CNNs) that automatically identifies various species of fishes and then classifies them into certain classes using a novel technique is introduced. In the proposed method, an autoencoder is employed to distinguish between seen and unseen species. To clarify, the autoencoder is trained to reconstruct the available species with high accuracy and filter out species that are not in our training set. In the following, a classifier based on EfficientNet is trained to classify the samples that are accepted by the autoencoder (AE), i.e. the samples that have small reconstruction error. Our proposed method is evaluated in terms of precision, recall, and accuracy and compared to the state-of-the-art methods utilizing WildFish dataset. Simulation results reveal the supremacy of the proposed method.

13. Underwater target detection algorithm based on improved YOLO v4 with semiDSConv and FIoU loss function Link

In this paper, issues of low-quality images due to the complex underwater environment, which makes applying these deep learning algorithms directly to process underwater target detection tasks difficult are addressed. An algorithm for underwater target detection based on improved You Only Look Once (YOLO) v4 in response to the underwater environment is proposed. First, a new convolution module and network structure is developed. Second, a new intersection over union loss was defined to substitute the original loss function. Finally, some other useful strategies to achieve more improvement, such as adding one more prediction head to detect targets of varying sizes, integrating the channel attention into the network, utilizing K-means++ to cluster anchor box, and utilizing different activation functions are integrated. The experimental results indicate that, in comparison with YOLOv4, proposed algorithm improved the average accuracy of the underwater dataset detection by 10.9%, achieving 91.1%, with a detection speed of 58.1 frames per second. Therefore, compared to other mainstream target detection algorithms, it is superior and feasible for applications in intricate underwater environments.

14. Multi-classification deep neural networks for identification of fish species using camera captured images Link

In this paper, the shortcomings of existing manual underwater video fish sampling methods, a plethora of computer-based techniques are proposed is addressed. However, there is no perfect approach for the automated identification and categorizing of fish species. This is primarily due to the difficulties inherent in capturing underwater videos, such as ambient changes in luminance, fish camouflage, dynamic environments, watercolor, poor resolution, shape variation of moving fish, and tiny differences between certain fish species. This study has proposed a novel Fish Detection Network (FD_Net) for the detection of nine different types of fish species using a camera-captured image that is based on the improved YOLOv7 algorithm by exchanging Darknet53 for MobileNetv3 and depthwise separable convolution for 3 x 3 filter size in the augmented feature extraction network bottleneck attention module (BNAM). The mean average precision (mAP) is 14.29% higher than it was in the initial version of YOLOv7. The network that is utilized in the method for the extraction of features is an improved version of DenseNet-169, and the loss function is an Arcface Loss. Widening the receptive field and improving the capability of feature extraction are achieved by incorporating dilated convolution into the dense block, removing the max-pooling layer from the trunk, and incorporating the BNAM into the dense block of the DenseNet-169 neural network. The results of several experiments comparisons and ablation experiments demonstrate that our proposed FD_Net has a higher detection mAP than YOLOv3, YOLOv3-TL, YOLOv3-BL, YOLOv4, YOLOv5, Faster-RCNN, and the most recent YOLOv7 model, and is more accurate for target fish species detection tasks in complex environments.

15. Machine learning to detect marine animals in UAV imagery: effect of morphology, spacing, behaviour and habitat Link

In this paper, a machine learning algorithm using a low-cost computer is developed. A convolutional neural network and tested its performance in: (1) distinguishing focal organisms of three marine taxa (Australian fur seals, loggerhead sea turtles and Australasian gannets; body size ranges: 0.8–2.5 m, 0.6–1.0 m, and 0.8–0.9 m, respectively); and (2) simultaneously delineating the fine-scale movement trajectories of multiple sea turtles at a fish cleaning station is trained. For all species, the algorithm performed best at detecting individuals of similar body length, displaying consistent behaviour or occupying uniform habitat (proportion of individuals detected, or recall of 0.94, 0.79 and 0.75 for gannets, seals and turtles, respectively). For gannets, performance was impacted by spacing (huddling pairs with offspring) and behaviour (resting vs. flying shapes, overall precision: 0.74). For seals, accuracy was impacted by morphology (sexual dimorphism and pups), spacing (huddling and creches) and habitat complexity (seal sized boulders) (overall precision: 0.27). For sea turtles, performance was impacted by habitat complexity, position in water column, spacing, behaviour (interacting individuals) and turbidity (overall precision: 0.24); body size variation had no impact. For sea turtle trajectories, locations were estimated with a relative positioning error of <50 cm. In conclusion, demonstrated that, while the same machine learning algorithm can be used to survey multiple species, no single algorithm captures all components optimally within a given site.