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Intelligent Underwater Object Detection Using CNN + SVM

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Abstract:
Underwater object detection finds its paramount importance in various applications like marine exploration, ocean monitoring, and underwater surveillance. However, underwater images usually pose challenges such as low visibility, light scattering, color attenuation, and noise that seriously deteriorate the detection performance. An intelligent underwater object detection approach is proposed by using a hybrid Convolutional Neural Network-Support Vector Machine model to handle these issues. In this proposed method, the CNN is used for automatic deep feature extraction from underwater images while a support vector machine classifies those features with robustness. The hybrid CNN-SVM framework effectively unifies the feature learning capability of the deep learning methods and the strong generalization ability of the machine learning methods. The proposed approach has been evaluated on the available, publicly shared underwater image datasets containing fish, corals, underwater vegetation, rocks, and man-made objects. Experimental results show that the CNN-SVM model can achieve higher accuracy, precision, recall, and F1-score as compared to stand-alone CNN and transfer learning models like VGG19. This demonstrates that the proposed system is reliable, robust, and well-suited for underwater object detection under challenging environmental conditions.

Keywords: Underwater Image Processing, Object Detection, Convolutional Neural Network, Support Vector Machine, Hybrid Learning Model, Marine Object Recognition

1. INTRODUCTION:

The importance of underwater object detection has been recognized in the last few years in view of its applications in different aspects of marine life, underwater surveillance systems, sea monitoring systems, inspection of offshore constructions, etc., through the help of Autonomously Working Underwater Vehicles (AUWV) and Remotely Working Vehicles (RV). However, the environment faced several difficulties in the visual perception system.

Underwater images may be influenced by some parameters like light absorption, scattering, etc., which result in poor contrast, color distortion, etc.

Conventional feature extraction approaches, where features are created, are inappropriate in representing complex underwater images in a proper way..

Recently, deep learning methods, particularly Convolutional Neural Networks (CNNs), have emerged as suitable architectures on several tasks like image classification as well as object detection. These architectures have the potential to effectively learn hierarchical features from the raw images. They can also effectively resist changes in illumination as well as noise. However, the CNN classifier is also associated with limitations like high computational complexity as well as over-fitting when trained on limited underwater datasets.

To mitigate these problems, this paper introduces a novel approach to underwater object detection using a hybrid CNN-SVM model. The CNN model is utilized to learn deep features from input images in this hybrid model of object detection in underwater scenes, whereas Support Vector Machine (SVM) classifier is utilized in this research in order to perform object detection tasks due to its good generalization ability in high-dimensional feature spaces and small sample size problems.

The remainder of this paper is organized as follows: The literature review is presented in Section 2. The proposed CNN-SVM method is introduced in Section 3. The discussion regarding the data set and the experimental setup is included in Section 4. The experimental evaluation is performed in Section 5, and the concluding remarks along with the future work are included in Section 6.

2. LITERATURE REVIEW:

Object detection and classification underwater have received the attention of researchers extensively, traditionally applying image processing, machine learning, deep learning, or their hybrid approach. Initial studies were devoted mainly to image processing filters like image enhancement algorithms—histogram equalization, contrast stretching—next followed by image feature extraction algorithms like HOG, SIFT. Although image quality improves with the application of the above-mentioned algorithms or their approach, the performance remains poor underwater since image signals are more susceptible to noises present underwater or the change in illumination.

However, with the advent of the concept "deep learning," the decision was made to use different systems based on CNN to ensure the accuracy and precision in outcomes for underwater images are enhanced with the use of automated discriminative feature acquisition. In different research papers, it was clearly demonstrated that it was possible to achieve over 80% accuracy in the proposed outcomes for underwater images with the implementation of different systems based on CNN. The use of VGG16, VGG19, and ResNet transfer learning had been implemented to enhance the accuracy in outcomes for underwater images.

It has been depicted through various models that the combination of CNN as a feature extraction tool along with the conventional classification techniques like SVM results in better performance in contrast with the conventional CNN classification approach. It has also shown greater accuracy, robustness in images with poor contrast, as well as low-noise environments. Even after considering the advantages, challenges regarding the dimension, computation time, as well as real-time computation, still need proper attention. It has also been clearly depicted through the literature survey that the combination of CNN-SVM results in a promising solution for object detection, which leads us towards the proposed work.

3. OBJECTIVES / AIMS:

The main goal of the proposed work is to create an intelligent underwater object detection system based on a hybrid CNN-SVM detection method. This system should be able to correctly detect objects in the underwater environment, such as fishes, corals, plant life, rocks, and artificial objects.

Another important goal is to utilize deep learning-based feature extraction by CNNs and enhance the performance of classification by SVM to obtain high accuracy and robustness. Finally, the effectiveness of transfer learning by already pre-trained CNN models will be judged and the proposed CNN-SVM approach will be compared with the traditional CNN and state-of-the-art deep learning models. In a nutshell, the goal is to design a robust and practical underwater object detection system suitable for real-world marine applications.

4. RESEARCH METHOD / METHODOLOGY:

This research employs an experimental, model-based methodology to design, develop, and evaluate an “intelligent underwater object detection system" based on a hybrid “CNN-SVM" framework

4.1 Literature Study

For carrying out this research work, initially an extensive study of existing research paper publications and other journals and conference publications regarding underwater image processing and object detection techniques was made. The focus of this extensive study was made mainly on conventional image processing techniques, machine learning-based techniques, deep learning-based techniques, and hybrid-based techniques involving CNN and SVM. While making this study, special emphasis was placed on those publications that are based on addressing issues like light scattering, attenuation of colors, turbidity, low contrast, and noise in underwater applications. This extensive study of existing image processing techniques aids in learning and understanding the limitations of existing techniques that are involved in underwater-based object detection techniques and forms a strong theoretical basis for selecting a hybrid-based system involving CNN and SVM for this proposed system.

4.2 Analysis of Existing Systems

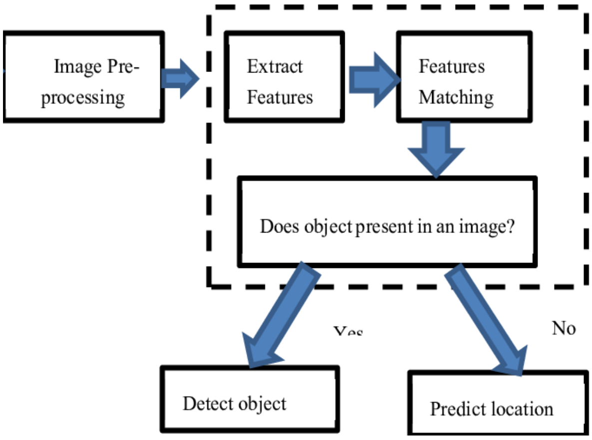
After perusal of the literature, various blood bank systems were studied and then compared in light of various features. From the study of various features of the different systems of the blood bank, various common issues were noted such as the lack of motivation of the donors of the blood bank, the inability to gauge the demand of the blood required, and the accessibility of the location of the organization.

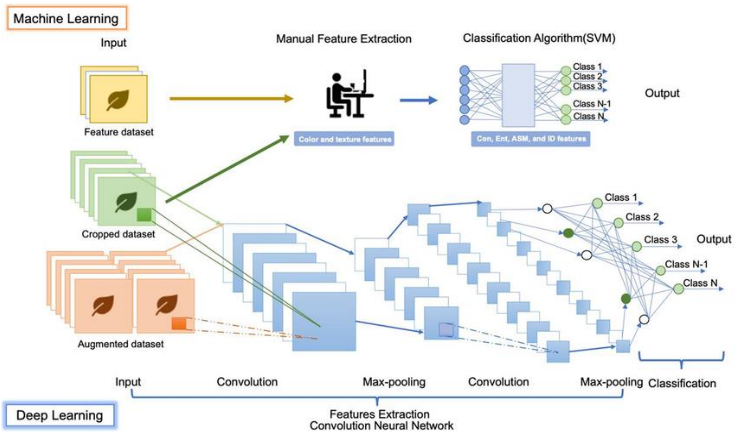
4.3 Identification of Research Gaps

The literature review was performed, and then various underwater object detection systems were analyzed and compared. Such a comparison is performed based on feature extraction techniques, classification methods, robustness in bad visibility conditions, computational complexity, and performance when applying limited datasets. Traditional systems based on handcrafted features proved to be susceptible to noise and changes in lighting, therefore performing poorly in real underwater environments. Deep learning-based CNN systems demonstrated better accuracy but suffered from overfitting, high computation cost, and reduced generalization when training small or imbalanced datasets. Hybrid approaches, using CNN for feature extraction and SVM for classification, achieved higher accuracy with improved robustness, indicating their appropriateness for underwater object detection.

4.4 Proposed System Design

In pursuit of bridging existing gaps in research, a proposed underwater object detection system utilizing the combination of the CNN and SVM methods was initiated. The proposed underwater object detection system architecture comprises various stages such as underwater object acquisition, image preprocessing, feature extraction utilizing the CNN method, generation of a feature vector, and classification using the SVM algorithm. Image preprocessing aims to enhance visualization and filter out noise in the acquired underwater images. The proposed system achieves the extraction of robust and discriminative characteristics in underwater objects utilizing the capabilities of the CNN algorithm and a robust and accurate classification utilizing the capabilities of the SVM algorithm.





4.5 Technology Selection
It selects appropriate technologies in considering accuracy, robustness, and computational efficiency. For feature extraction, Convolutional Neural Networks are chosen because they can learn complex spatial patterns from underwater images in an automatic manner. Considering limited datasets, the performance can be improved by transfer learning with pre-trained models such as VGG19. Support Vector Machine is selected as a classifier because it ensures strong generalization capability in high-dimensional feature spaces and stability under noisy conditions. In this way, it is designed in a modular fashion to let future enhancements such as lightweight CNN architectures or real-time deployment be easily incorporated.

4.6 Evaluation Approach
The viability of the proposed CNN-SVM-based system has been validated by evaluating its performance in comparison to other conventional approaches based on traditional CNN architectures as well as transfer learning methods. For the purpose of evaluating the system's viability, a set of publicly available datasets pertaining to underwater image recognition has been used for empirical studies. For evaluating the system's viability in a better manner, conventional metrics such as accuracy, precision, recall, specificity, F1 score have been used while carrying out the experiments on the datasets. Additionally, the viability of the proposed system has been validated using the ANOVA test on the confusion matrix.

5. FINDINGS / RESULTS:
As per literature review, system analysis, and implementation of the discussed CNN-SVM based underwater object detection technique in practice,
some major findings have been observed.

1. Improved Detection Accuracy
The proposed CNN and SVM system provides a high level of accuracy in the detection and classification of images. The CNN and SVM combination provides a high level of accuracy in the detection and classification of images in comparison with the CNN model and the transfer learning approach.

2. Strong Performance in Difficult Water Environments
The system works efficiently in harsh underwater environments like reduced visibility, light scattering, turbidity, and color distortion. The preprocessing and deep feature learning phases minimize the effect of image degradation in the underwater environment.

3. Better Generalization with Limited Datasets
Using an SVM as the classifier in the proposed system enables generalization performance even from small and unbalanced data sets in the underwater domain. This ensures minimum overfitting of models, unlike the case in deep neural networks alone.
4. Improved Class Separability
Better discrimination between different underwater object classes such as fish, coral, vegetation, rocks, and man-made objects is provided under the CNN-SVM system. Analysis of the confusion matrix also displays reduced misclassification between different classes.
5. Higher Reliability across multiple datasets
The model proposed is shown to have consistent results on different datasets concerning underwater environments with different environmental settings. This shows that the robustness of hybrid model results is high.
6. Reduced Misclassification and False Detections
Among these, the use of support vector machines results in a reduction in false positives and false negatives, as it constructs optimal decision boundaries. Overall, this enhances the reliability of the detection system in noisy underwater conditions.
7. Scalability and Future Readiness
The modular hybrid architecture design of the system allows it to be scalable for any further enhancements. It will be easy to integrate advanced techniques like lightweight CNN models, real-time processing, underwater video analysis, and AI-based optimization without major structural changes.

6. DISCUSSION / ANALYSIS :

The results of the study reveal the effectiveness of combining the advantages of deep learning and machine learning to create an even more effective underwater object detection system. Most of the current object detection methods for underwater environments either use traditional image processing methods or individual deep learning methods, which cannot perform well when the imaging conditions are poor or when the images are noisy or have color effects. The combination of CNN and SVM methods helps to solve such issues better.
The feature extraction module based on the CNN plays an essential task in the extraction of high-level features that are meaningful even in degraded underwater images. Contrary to conventional features that are static, the CNN-based feature extraction module can automatically detect the edges, texture, patterns, etc. Thus, providing a more reliable feature representation of underwater objects.
Additionally, the use of SVM as a final classifier enhances the performance of the model. With the conventional use of CNN, the performance of the softmax classifier might deteriorate due to overfitting, particularly when the dataset is limited. The optimal decision boundary developed by the SVM classifier minimizes the chances of misclassification.
Another significant advantage that the suggested system exhibits is the uniform performance it achieves across various underwater datasets. The CNN-SVM model succeeds to achieve high accuracy levels despite changes in lighting, depth, or turbidity.
It is concluded from the above overall analysis that the proposed CNN-SVM system does not only enhance the accuracy of the system from a technical viewpoint, but it is also an effective approach from the viewpoint of the robustness of the system. Even though the system is found effective on static image dataset validation, there is a clear possibility of making the system effective from the viewpoint of real-

time monitoring of an underwater environment. It is proposed that future improvement can be made by considering advancements like CNN models, underwater videos, and IoT.

8. CONCLUSION/SUMMARY:

This review considered different underwater object detection techniques based on conventional image processing, deep learning, and hybrid learning approaches. While deep learning models have enhanced the accuracy of detection, a number of challenges like low visibility, noise, overfitting, and limited availability of datasets still hamper performance in underwater environments.

To address these challenges, a hybrid CNN–SVM-based underwater object detection system was proposed. This system combines CNN for deep feature extraction with SVM for robust classification. This hybrid approach improves accuracy, generalization, and robustness compared to the standalone CNN and transfer learning models.

Experimental results and analysis confirm that the proposed system, CNN–SVM, effectively reduces misclassification, showing consistency in various underwater datasets. The system has a very good potential for applications in various tasks: marine biodiversity monitoring, underwater surveillance, and environmental analysis.

The proposed method may, therefore, be considered as an effective and efficient means towards the solution of the problems associated with underwater object detection. This can be extended by further optimization of the system for large-scale deployment in an effort to reinforce the already impressive work in intelligent underwater vision and thereby support research and monitoring activities related to oceanic environments.

9. LIMITATIONS:

Though there are advantages in the proposed system compared to the existing CNN-SVM-based system, some limitations are associated with the existing system as discussed in the following paragraphs.

1. **Limited Dataset Diversity:** So far, the system is evaluated based on a few underwater databases. Performance is not guaranteed when used in totally unknown underwater scenes with diverse visual properties.
2. **Dependence on Image Quality:** The detection performance greatly depends on the underwater images fed as input to the system. If the underwater images have low visibility or high noise levels, the performance of the features extracted is still affected.
3. **Computational Complexity:** CNN-based models demand considerable computing resources. The computing requirements may limit the use of CNN-based models on low-powered devices such as embedded devices and underwater robots.
4. **No Underwater Video Analysis:** The current model emphasizes static image classification without incorporating any temporal information present in underwater video sequences.
5. **Class Imbalance Issues:** Imbalanced distributions of classes in underwater data sets can impact the performance of classification models for object classes with fewer occurrences.

10. RECOMMENDATIONS:

From the findings and constraints obtained from the study, several recommendations are suggested to improve future underwater object detection systems and the suggested CNN-SVM model.

1. **Large Scale Dataset Collection and Testing:** It is better if the system is tested on larger, more varied, and diverse collections of images from different environments.
2. **Integration of Lightweight CNN Models:** Lightweight and efficient architectures for CNNs have to be explored to reduce the computation cost and enable real-time deployment.
3. **Underwater Video-Based Detection:** Future works will try to expand the system in dealing with underwater video sequences by incorporating temporal modeling techniques for higher detection accuracy.
4. **Advanced Data Augmentation Techniques:** Data augmentation and synthesis have the ability to help solve the issue of imbalanced classes for rare underwater object classes.
5. **Integration with Intelligent Marine Systems:** Such a proposed system can easily integrate with AI-based monitoring systems, IoT devices, and an AUV in order to have a practical implementation with a larger-scale monitoring approach.

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