Underwater Image Processing in Detection of Polymetallic Nodules

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Abstract. Polymetallic nodule detection underwater is faced with the extreme conditions like low visibility, various light intensity and complex textures of underwater seabed. In this study, we suggest a end-to-end machine learning and deep learning framework to enhance the underwater image analysis for polymetallic nodule detection. The mechanism of the proposed method consists of the following three stages: image recognition, boost and object detection. First, an SVM classifier is used to classify images to four types uniform illuminated, low illuminated, disturbed and ground nodules to enable a targeted processing. The low-lit images are enhanced by a CNN which can significantly outperform the traditional Contrast Limited Adaptive Histogram Equalization (CLAHE) in terms of retaining the structure of the images and enhancing visibility. Finally, a YOLOv5-based object detection model is trained with a customized dataset to effectively detect and localize the polymetallic nodules in multiple underwater situations. A comparison between the automated Nodule Hunter (with a support vector machine (SVM) classifier), CNN network, and the YOLOv5 is carried out in experiments, and the superiority results in the classification accuracy of SVM, the edge detail of the clear image of CNN, and nodule detection precision of the YOLOv5 are compared. The proposed automated pipeline simplifies the underwater mineral prospecting process, and provides more robust and time-effective resource identification for deep-sea mining.

Keywords: Underwater image processing, polymetallic nodules, machine learning, deep learning, SVM, CNN, YOLOv5, image enhancement.

1 Introduction

The development of deep-sea mineral resources has recently attracted much attention, and polymetallic nodules constitute a major deposit of rare metals. These nodules, discovered on the marine floor, carry four of the important metals, that is Mn, Ni, Co and Cu that are indispensable for the industry. However, the identification and analysis of such nodules is faced with significant difficulties because of the complicated marine environment, for example deficient luminosity, turbidity and diverse seabed texture. Correct classification, optimization and detection of PMN in UWIs are crucial for promoting deep-sea mining exploitation and marine research.

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Previous studies on underwater image processing have used different methods to classify and improve shadowy images. Methods such as Decision Trees, K-Nearest Neighbors and Logistic Regression demonstrated low accuracy owing to high variabilityin underwater imagery. Advanced machine learning methods such as SVM (Support Vector Machine), Random Forest and such have achieved better classification results, but it is dependent on the the size and complexity of 15 the datasets. Image enhancement techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) have been applied to enhance the visibility of low illuminated images, however, the structural details are not always well preserved.

In our work, The Proposed Solution is divided into three-stage pipeline to enhance the detection of polymetallic nodules in the underwater images, which are as follows: classification, enhancement and object detection. First of all, the SVM based classifier was utilized to classify images into four categories: uniformly lit underwater nodule type, low lit underwater nodule type, ground nodule type, and disturbed underwater image type [2]. This classification process guarantees that the processing of images is matched to their actual content. For a low-lit classified image, a CNN-based enhancement model is performed for better clarity and structural preservation. Last, an object detection task is formed by using a YOLOv5 model, trained on a tailored dataset, to locate polymetallic nodules in evenly-lit, disturbed, and enhanced images.

The research tackles the fundamental issue to improve analysis of underwater images for polymetallic nodule detection, through the use of robust machine learning methods. We also perform extensive comparison experiments and show that SVM outperforms other classifiers in scalability and generalization. Furthermore, the performance of CNN-based enhancement is much better than that of CLAHE in the sense of PSNR and SSIM, which leads to better quality of reconstructed image. Lastly, the detection model YOLOv5 achieves high accuracy in nodule identification and improves the ability for underwater mineral exploration.

By constructing an efficient classification, enhancement, and detection pipeline, this work is beneficial to promote the development of underwater image processing. This method would provide a scale able and accurate means of polymetallic nodule identification thereby enabling a higher degree of automation in deep sea exploration and resource assessment.

2 Related works

Existing literature in the progress of underwater imagery processing, numerous underwater image processing problems have been studied to compensate for the degradation factors in UWIs, such as low light, scattering and noise.

A significant contribution in this area is the work of Prabhakaran et al. (2022) deploy a machine learning method to study polymetallic nodules from underwater images and videos. In their work, the authors described a scheme of three stage of image processing by applying techniques such a histogram equalization and CLAHE (Contrast Limited Adaptive Histogram Equalization) to improve the image quality [1]. They cascade the classifiers according to the undilated nodule search region, which optimizes the detection efficiency and the detection rate of the nodules is increased a lot. Haar-Cascade method was proposed by Viola and Jones [11], which efficiently withstands classifiers to cascade structure and speeds up the detection process through paying attention to the region of interest (ROI), and the nodule detection rate is substantially improved.

In another important work, Ancuti et al. (2019) proposed a novel technique to estimate local backscattering light in underwater imagery. These kinds of approaches commonly estimate global image wide backscattering which do not handle non-uniform illumination due to multiple lights sources [4]. In their local backscattering estimation, small and large patchesize combination provides accurate underwater image dehazing result. The technique together with a transmission map estimated by applying the dark-channel prior results in favourable performance with respect to several existing underwater enhancement methods, in the absence of underwater lighting conditions.

Han et al present another solution for the underwater image processing. (2020) that specifically addressed underwater object detection with deep convolutional neural networks (CNN) [6]. Their approach uses combined max-RGB and shades of gray methods for image enhancement, then employs CNN for the detection and classification of underwater targets. The authors suggested two enhanced CNN models which achieve surpassing performance over classical detection models, like fast RCNN, faster RCNN, YOLO V3, in speed and precision of detection. Such method is particularly useful in any real time UNDEX work where the detection speed and accuracy are of great importance.

A meta-analysis by Jian et al. (2020) provides a complete overview of models of image processing and analysis for underwater [7]. The authors explored a group of challenges of underwater imaging such as lighting scattering, absorption and complexity of underwater background. They considered several processing techniques, including enhancement, segmentation, and color constancy, and provide an analysis of potential future works to improve underwater vision devices.

2.1 Motivation and contribution

The study of underwater mineral resources, in particular polymetallic nodules, is of a great interest because they can potentially compensate an increasing demand of critical metals, such as nickel, cobalt and manganese. They are critical technologies for renewable energy, battery manufacturing, and a range of industrial applications. These resources are of high significance, but their survey and exploration is, however, hampered due to the undersea environment. Poor visibility and non-uniform lighting, and the lack of robust methods to reliably detect and map these formations, are still the major challenges. This need supports the motivation of the current work to address these challenges and contribute to a better site for the online exploration underwater.

Prior works have provided fundamental insights in this regard, but have primarily considered separate aspects of imaging for underwater scenarios. For instance, Wang et al. (2019) emphasized the need to categorize underwater for underwater images with respect to their visual quality; however, no other steps were considered, including enhancement and detection [3].

Also, the study of Ancuti et al. (2020) proposed enhancement techniques concentrating on providing further visibility in the underwater images [4]. Though successful in some scenarios, these techniques did not necessarily transfer well across different underwater conditions.

On the detection side, for example, Redmon et al. (2016) proposed the YOLO object detection framework, which was proved to have high performance in most general cases, but faced great challenges in underwater cases [5]. These studies accentuate the progress in classification, enhancement and detection taken alone, but also make it clear that a unified system should be developed to address them all together.

In this work, we propose an integrated underwater image processing system by concatenating the three essential process the classification, enhancement, and detection—into one framework. Our system starts with a strong image classification step using the principles shown in Wang et al. (2019) for classification of underwater imagery into types as well-lit and poorly lit [3]. This classification is used in the image enhancement part to make it adaptable to the typical challenges of each type.

For enhancement, a new deep learning-based model is implemented by comparing it with some Traditional methods such as Histogram Equalization proposed in Prabhakaran et al. (2022), obtaining a more consistent results with sharper results by improving contrast, colour distortion, clarity etc. [1].

At the last stage, we employ the object detection architecture YOLOv5 proposed by Redmon et al. (2016) and is tailored to the specific application of polymetallic nodule detection in underwater, [5].

The emphasis of this study on practical application is a large contribution. Unlike a lot of papers that are still theoretical, this paper implements its findings in an accessible software package. The interface is created by Python's Tkinter library, making it easy to handle the visualization and post-processing of the underwater images, facilitating the development and application of the tool to real world applications by researchers/practitioners with small technical background.

By solving fundamental problems in underwater imaging, this work has immediate applications to the enhancement of the quest for accuracy and consistency in exploration efforts, as well as applications to overarching aims such as diminishing reliance on terrestrial mining, impoverishing environmental impact, and advancing sustainable resource utilization. It connects academic research and industry applications and will lead to more efficient and environmentally-friendly drilling for the huge resources found under the ocean [8].

3 Problem statement

The detection of polymetallic nodules in subsea environments is a challenging task due to low visibility, varied lighting conditions, and complex seabed textures. Traditional classification approaches fail to achieve high accuracy, particularly for low-lit, and disturbed underwater images. The current enhancement methods are not able to maintain the image quality, hence affect the performance of the detection. Moreover, underwater object detection is challenging as a result of the noise, occlusions, and varying background lighting.

To handle these problems, in this paper, we propose a three-stage method including classification, enhancement, and detection. First, an SVM classifier is adopted to classify the images into four types of images: underwater nodules with uniform lighting, underwater nodules with low lighting, ground nodules, and disturbed underwater images [Fig. 1]. Then, a CNN-based refinement model is utilized to enhance the visibility of weakly illuminated images while the key structures are preserved. Lastly, an object detection model is established based on YOLOv5 to accurately detect polymetallic nodules in normal, disturbed, and enhanced images.

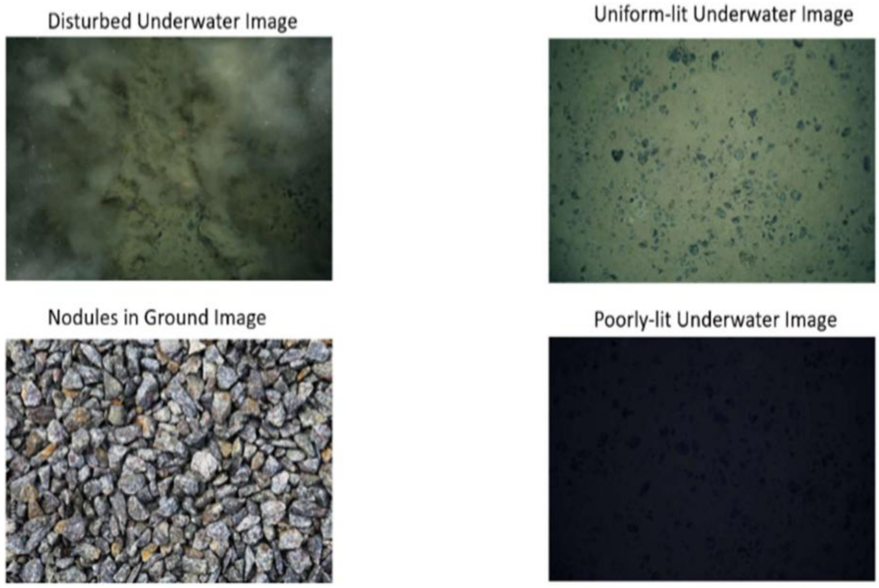

Fig. 1. Types of Images used in the Process collected from Reputed Source. [2]

By incorporating machine learning to each stage, this study aims to offer a reliable and scalable method for underwater image processing, to enhance the accuracy and efficiency of polymetallic nodule detection. The present contribution constitutes an advance toward the development of deep-sea exploration robotic systems, being also of interest for mining resources from the deep seabed in a sustainable manner.

3.1 Proposed solution

The Proposed Solution is a in three-stage pipeline to classify, enhance and find-under-water-images polymetallic nodules [Fig. 2]. The method uses machine learning and deep learning methodologies to automate the image processing procedure, and to enhance detection performance.

The classification stage is divided into 4 categories, including uniform-lit, poor-lit, ground-nodule, and disturbed-image. This classification is done using an SVM classifier, which is adopted for its high accuracy and generalization ability. In extensive testing, the SVM model outperformed all others, achieving 99% accuracy on large datasets. SVM did not exhibit the same amount of overfitting as Random Forest and achieved the stable level of performance on different sizes of datasets and with different variations of images.

The poorly lit images detected in the second stage are enhanced in 7 using a CNN model. This CNN regresses to produce enhanced visualization by transforming dim images into brightened images but with structural information retained. Experimental results demonstrate the superiority of the CNN-based method compared to traditional enhancement methods such as CLAHE in terms of key image quality metrics such as Peak Signal-to-Noise Ratio (PSNR),

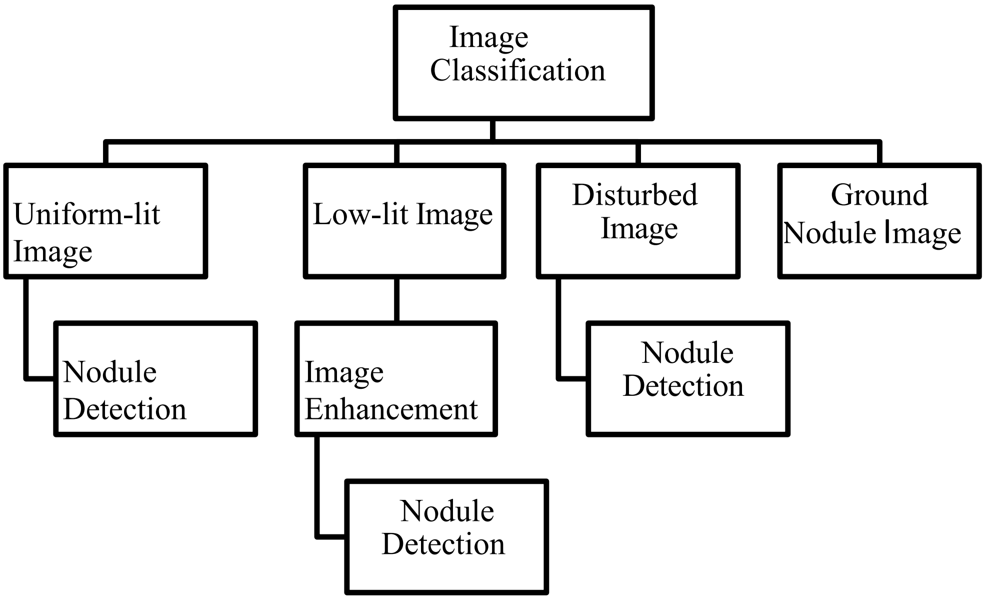

Fig. 2. Block Diagram of the Proposed Solution for Underwater Image Analysis.

SSIM and Histogram Correlation. The quality of images has greatly improved with the CNN model, which may facilitate in the analysis of nodules detection.

The third phase is object detection of polymetallic nodules in the images with YOLOv5. This model is based on a custom dataset of annotated underwater images and is adapted for real time detection. The performance comparisons were made in challenging underwater scenarios with changing illumination, and show that YOLOv5 is able to successfully detect and localize nodules. Images with nodules are saved for later analysis when found.

Everything is built in a completely automated pipeline. At first, the images are classified to four categories using the SVM mode and are stored to the corresponding folder disturbed, uniform lit, low lit, and ground nodule. Then use the same CNN model for better illumination and save them separately. At last, all the images of uniform-lit, disturbed and enhanced are input to the YOLOv5 model for the nodule detection. The detected nodules are stored in an assigned output directory.

For example, in underwater image classification, our pipeline achieves solutions that are more accurate classifiers, sharper images, and more accurate nodule localization. The method offers a scalable and effective way to handle the analysis of underwater images that helps the deep-sea exploration and mineral resource evaluation.

3.2 System design

The system architecture is based on an automated processing pipeline of underwater images for polymetallic nodule classification, enhancement and detection. This organized system is composed of three major steps for an organized workflow. First the system separates the images into light and content conditions and divides the input images into uniform-lit, under-lit, ground-nodule, and disturbed. This will simplify further processing. Then, the dim images are enhanced based on CNN to make the dim object visible. Finally, a YOLOv5 object detection model is applied to detect and locate polymetallic nodules. Those steps in the pipeline are all linked together, so the output of one is the input to the next. The method can achieve efficient encoding and accurate detection, which offers a useful solution to problems of underwater image processing.

3.3 Image Classification

Table. 1. Performance Comparison between different Classification Models.

Classification Model	Accuracy	Cross Val. Mean	Time Taken to Train (sec)
Support Vector Machine	0.9326	0.9406	6.14
Random Forest	1.0000	0.9887	13.09
Decision Tree	0.9775	0.9605	6.14
Gradient Boosting	0.9888	0.9547	1860.31

Neural Network	0.8315	0.8412	13.30
K-Nearest Neighbors	0.3820	0.3653	0.77
Gaussian Naive Bayes	0.9213	0.9262	0.79
Logistic Regression	0.8090	0.8783	1.35

This Proposed solution was designed to tagged the polymetallic nodule images to one of the following four categories: Uniform- lit, Poorly-lit, Ground Nodule, and Disturbed-Image with machine learning approaches. The classification phase started by extracting HOG features from the images and we trained several models (SVM, Random Forest, Gradient Boosting, Decision Tree, Neural Network, KNN, Logistic Regression).

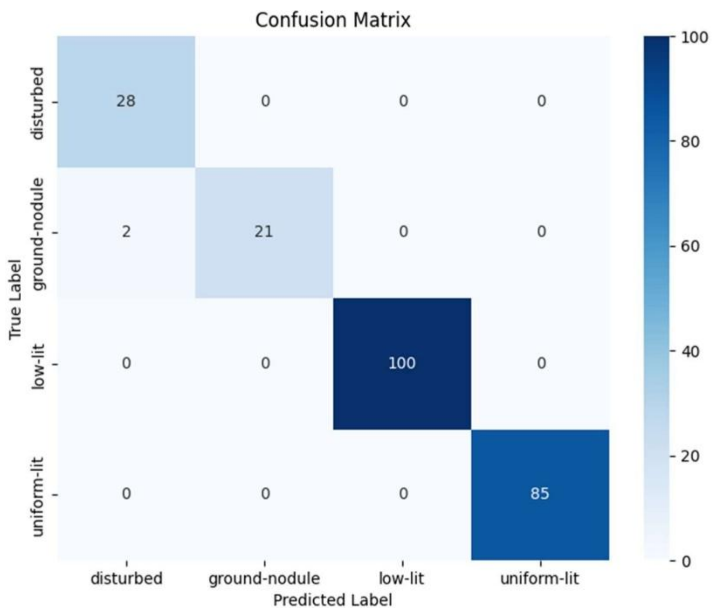

Fig. 3. Confusion Matrix of SVM Classification model in Second experiment.

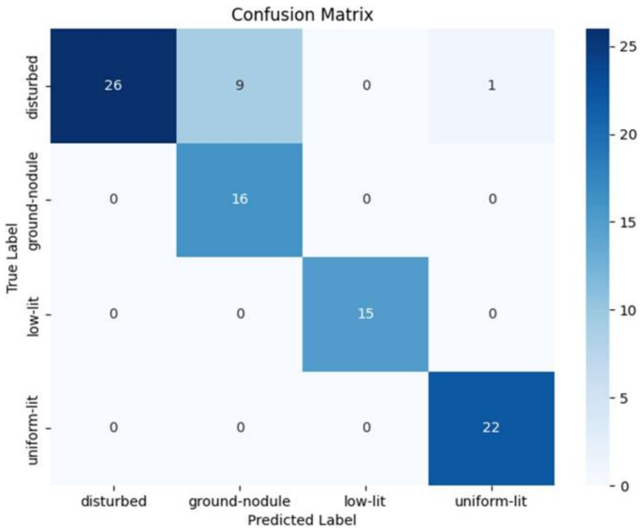

Fig. 4. Confusion Matrix o Random Forest Classification model in Second experiment.

In the first experiment using a 500-image dataset, Random Forest was the most accurate model (Table 1), exhibiting 100% accuracy in all performance measures. SVM also performed close to DEC with an accuracy of 93.26% showing stable precision, recall and F1- score. Other models such as the Gradient Boosting (98.88%) and Decision-Tree (97.75%) models had decent results, while the K-Nearest Neighbors (38,20) and the Nearest Network (83.15%) had difficulty to generalize. Logistic Regression (80.90%) also seemed to be restrained due to the complexity of the dataset.

To evaluate the scalability of the models, a second experiment was carried out with 1200 images to see how they could cope up with much larger data sets. Random Forest overfitted having an accuracy of 100% on the training set and an accuracy of 89% on the testing set displaying the worst performance regarding generalization [Fig. 4]. SVM, in contrast, kept solid performance but saturated at the testing set at 99% accuracy, showing the good scalability power without overfitting [Fig. 3]. This indicated that, while Random Forest was optimal for smaller dataset, accuracy of SVM was superior for larger one, which provided a stable classification accuracy with increasing data size.

To improve SVM performance, we had also tuned the hyperparameters of the classifier using grid search. The radial basis function (RBF) kernel was selected because of its capability to address non-linearity of data distribution. The regularization parameter C was optimized in 0.1, 1, and 10, considering the maximization of margin and accuracy. The gamma parameter, which determines the curvature of the decision boundary was also tuned with values including ‘scale’, 0.001, 0.01 and 0.1. The results proved SVM to be the most excellent classifier for polymetallic nodule images, precisely provided sound accuracy and generalization to the different numbers of samples per class scenarios. For its ability to scale and avoid overfitting, SVM is the best modelling technique in this classification.

3.4 Image Enhancement

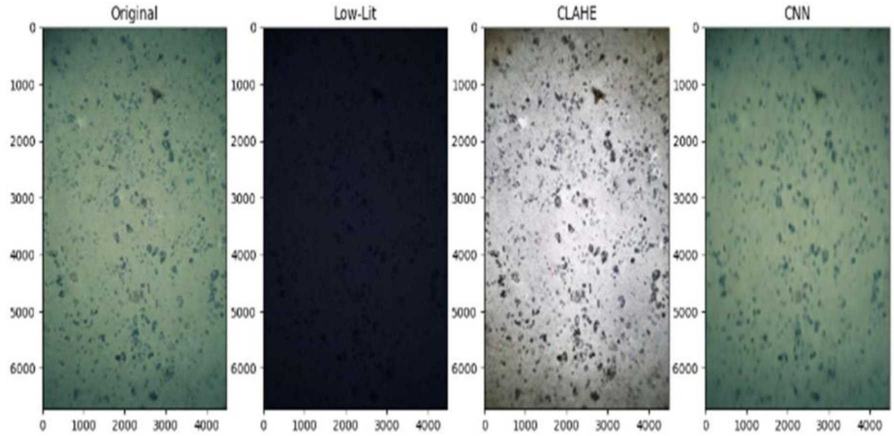

Fig. 5. Visual Comparison. between CNN and CLAHE for Image Enhancement

The CNN-based image enhancement algorithm also achieves higher performance than the original CLAHE algorithm in the underwater image process [Fig 5]. It is concluded from the Analysis that CNN performs superior in major quality metrics such as PSNR, SSIM, histogram correlation, NRMSE and hence CNN is the best option for image enhancement. also, CNN had a PSNR of 28.51, much better than

10.26 by CLAHE's noise-free at 19.64, while the CNN method yielded cleaner images. Also, CNN SSIM (0.867), is capable of retaining the integrity of the structure of image, whereas, CLAHE (only 0.05) is poor in keeping image details. The CNN method also improved its histogram similarity (correlation = 0.99) with respect to CLAHE, indicating that it possibly preserves the color and intensity of the image better than does CLAHE. NRMSE of 0.077 is obtained 7.5, Elements and Analysis from it causes the less error in the image, which further emphasizes that CNN performs better.

Even though CLAHE provides better contrast enhancement, it does not compensate for the less appealing image quality, by which CNN is superior [Table 2]. Finally, the CNN-based enhancement technique can be integrated into the pipeline for significantly improving image quality so that it becomes more suitable for underwater image restoration and subsequent analysis.

3.5 Nodule Detection

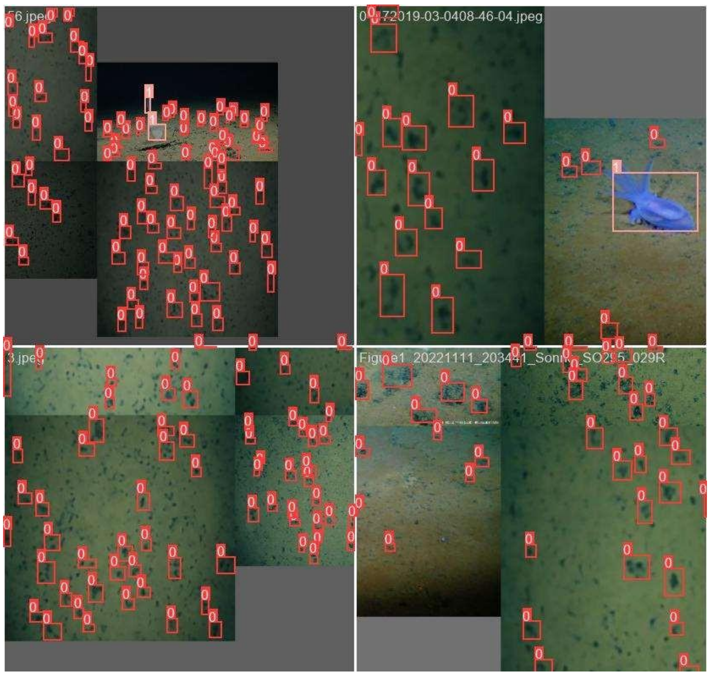

Fig. 6. Training Result of YOLOv5 model which detects the Nodules and Disturbance.

In the third step of our process, we have to find polymetallic nodules from these images. To do this, we employ a deep learning model called YOLOv5 that is trained to detect objects in images.

Step 1: Create a Custom Dataset for Training The custom dataset is prepared into the training stage with the use of "LabelImg" tool to annotate images of nodules. It gives us the facility to create manual annotations of the nodes by drawing bounding boxes on them and we obtain the text-files and classes that describe the manual annotations of theses nodes.

YOLOv5 requires annotations in a particular text format where the coordinates and the dimensions of the bounding box are represented in normalised form with respect to the image. Images are organized into two separate folders for training and validation using a Python script and dataset. yaml-file (obj.data): A new config file (e.g. obj.

Then you may train the YOLOv5 model using the custom dataset. This requires that the labelled images are fed into the model which learns how a PDCS nodule is identified using the bounding box annotations. This model is trained for several epochs (30 Epochs using Batch size 16) and performance is measured with numerous metrics. Training is the adjustment of the model's internal parameters to achieve the best performance in the detection of nodules.

After the model is trained, it can be used to identify nodules in images that have been processed through previous stages of the pipeline. This model infers on these images and draws bounding boxes around the detected nodules [Fig 6]. The output, with the images and the drawn bounding boxes, are stored in a destination folder (runs/detect/exp) for later use.

At the completion of the pipeline, A Trained YOLOv5 model was successfully developed to detect polymetallic nodules from the output of the previous pipeline stages. This automated detection step is an improvement to the flow in the project, and is also vital as nodules will be analyzed further if detected.

4 Final Workflow

The entire process is put in a one joint pipeline for automation of work process, from imaging classification to nodule detection. The pipeline has three main components, namely Image Classification, Image Enhancement and Nodule Detection.

At the first stage the images from the source folder are sorted into the following categories: "Uniform lit", "Poorly-lit", "Ground-Nodule", or "Disturbed Image". The type of classification is an SVM, which will be done by a pre-trained and saved SVM classifier model, using the library “joblib”. The classifier separates the images by lighting type and content, and moves each image to the respective folder for processing.

When images are classified as “Poorly-lit” or “Low-lit,” they are channeled into the second stage of the pipeline— Image Enhancement. Here us the CNN-based enhancement model (and saving as enhancement_model. keras) is used to enhance the quality of the images. This model improves images with poor lighting conditions and harmonizes them to evenly illuminated images to better facilitate subsequent analysis. You can save the improved pictures in the ""enhanced images"" folder.

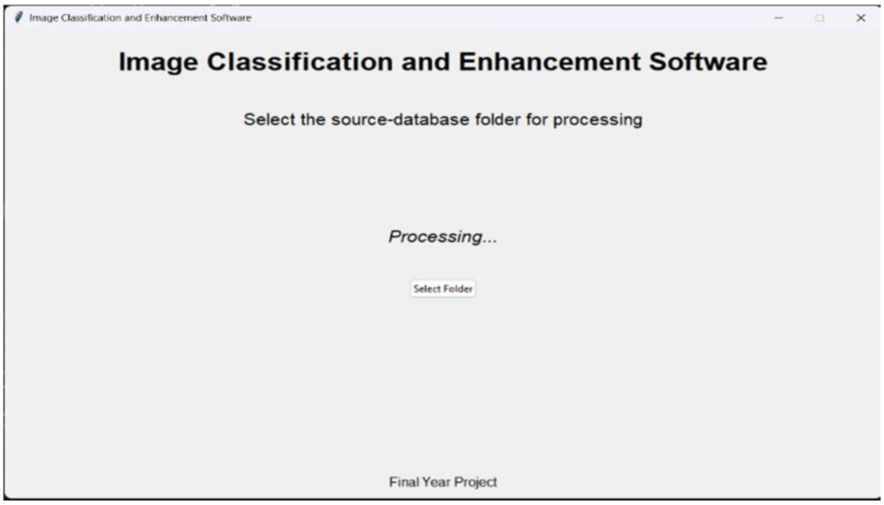

Fig.7. Graphical User Interface for the Underwater Image Processing Pipeline using Python Tkinter GUI

The last phase is Nodule Detection. The photographs in the directories ["uniform-lit", "disturbed", and "enhanced-images"] are inputted into a YOLOv5 derived nodule detection model. This network was trained on a homebuilt dataset of underwater images with polymetallic nodules, and can therefore properly recognize the nodules. The images are orchestrated by the YOLOv5 model, marks the nodules found in a picture and puts the new image in the "destination" folder.

All these procedures are incorporated to a Python-based Tkinter GUI that allows both intuitive and user-friendly interface for users [Fig 7]. On the GUI main interface there is a button labeled as "Select Folder", to be used to select the folder that contains the database of the images. The FD-LPL system also automatically processes images in the selected folders area and organizes images to corresponding folders, namely, original images, enhanced images, images after classification, images with nodule information and final classification reports.

This pipeline not only perfectly integrates all procedures into a whole but also can process underwater images efficiently and automatically, thus contributes to an organized and systematic exploration for polymetallic nodules.

5 Conclusion

This study successfully established an automatic pipeline to process underwater images for detection of polymetallic nodule applying machine learning and deep learning methods. The classifier SVM separated the images well according to lighting conditions and bottom types, ensuring proper processing. The CNN-enhancement model visually enhanced the visibility of dark images while maintaining structure information and outperforming conventional method such as CLAHE [Table 2]. Moreover, the YOLOv5 detection model finetuned to a specific dataset was sufficiently accurate in nodule identification for such diverse types of the underwater scenes [Fig 8].

Table. 2. Performance Comparison between CLAHE and CNN for Image Enhancement.

Parameters	CLAHE	CNN
PSNR	10.2576	28.5137
SSIM	0.05016	0.8673
MSE	6128.0248	91.5609
NRMSE	0.6316	0.0772
Histogram Correlation	-0.0836	0.9896
Contrast Enhancement Ratio	13.4641	3.8840

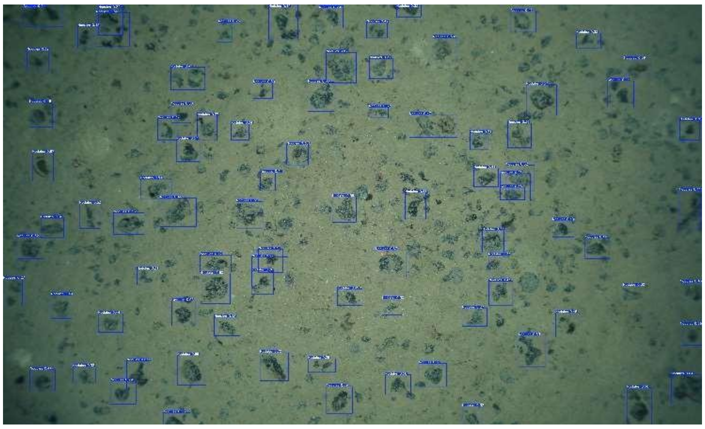

Fig.8. Trained YOLOv5 model detecting around 88 Nodules in the Given Image.

It functions as an efficient and user-friendly solution to the automation of seabed exploration, incorporating classification, enhancement and detection into an all-in-one Tkinter interface. the results verify that the pipeline can result in better detection performance, image quality, and analysis efficiency, which demonstrates the feasibility and effectiveness of the approach for deep-sea mineral resources identification. Further work includes diversifying training data sets, refining online processing approaches, and extending the system to larger scale underwater exploration tasks.

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