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# ADVANCES IN DEEP LEARNING FOR UNDERWATER OBJECT DETECTION AND CLASSIFICATION: CHALLENGES, ARCHITECTURES, AND APPLICATIONS

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**Abstract:** The architecture, training techniques, and performance assessment of deep learning models for underwater item detection and classification are the main topics of this review study. It offers a thorough examination of neural network architectures specifically suited for recognising and classifying submerged objects, including artificial structures, detritus, and aquatic life. The study describes the training procedures, emphasising parameter optimisation and prediction performance enhancement, and highlights data pre-treatment techniques that are crucial for optimising model input. It also examines the evaluation measures used to gauge the model's efficacy and accuracy in actual underwater settings. The difficulties specific to underwater imaging are examined closely, including environmental influences and restrictions related to submerged settings. Lastly, useful insights into the practical utility and limitations of these models are provided by discussing their deployment considerations in real-world circumstances. With its thorough synthesis of recent developments in deep learning-based underwater object recognition and classification, this study offers a comprehensive knowledge of the field's achievements and difficulties.

## Introduction:

Identifying and classifying objects in the vast and ever-changing underwater environment presents significant challenges due to factors such as varying light conditions, low visibility and constantly shifting aquatic ecosystems. Traditional detection methods, though effective in controlled settings, struggle to adapt to these complexities, highlighting the need for more advanced and resilient solutions. Deep learning has emerged as a powerful approach, enhancing underwater object detection and classification with greater accuracy and efficiency.

This research examines the application of deep learning for identifying underwater objects and mines, focusing on the development of innovative techniques and neural network architectures suited for submerged environments. It explores models such as YOLO (You Only Look Once), Convolutional Neural Networks (CNNs), and Region-based CNNs (R-CNNs), highlighting their adaptations to overcome the unique challenges of underwater detection. These models play a crucial role in underwater security and environmental monitoring, aiding in the identification of mines, debris, marine life, and artificial structures.

The paper also explores the essential role of data pre-processing and training methodologies in the success of deep learning models. Overcoming underwater imaging challenges like noise, low resolution, and fluctuating lighting conditions requires advanced techniques to ensure accurate object detection. The performance of these models is assessed using metrics such as accuracy, Intersection over Union (IoU), and Floating-Point Operations Per Second (FLOPS), providing insights into their real-world application efficiency.

By synthesizing recent advancements and examining practical deployment considerations, this paper provides a comprehensive overview of the current state-of-the-art in underwater object and mine detection using deep learning. It highlights the transformative potential of these technologies while discussing their limitations and future directions for improving the robustness and reliability of underwater detection systems in challenging environments.

## 2.2 Review Process

The current research rigorously performed an exhaustive classification and analysis of the available literature. Figure 1 illustrates the various stages of the review process, which comprised of total number of publications across 4 different disciplines with increasing order of granularity which include: (1) Object Detection, (2) Underwater Object Detection, (3) Underwater Naval Mine Detection and (4) Underwater Naval Mine Detection using SONAR images and OPTICAL images.

Google Scholar (scholar.google.com) emerged as a valuable resource, facilitating the compilation of subject-related literature from a diverse range of sources. The review of collected literature was comprehensive, extending up until 2024.

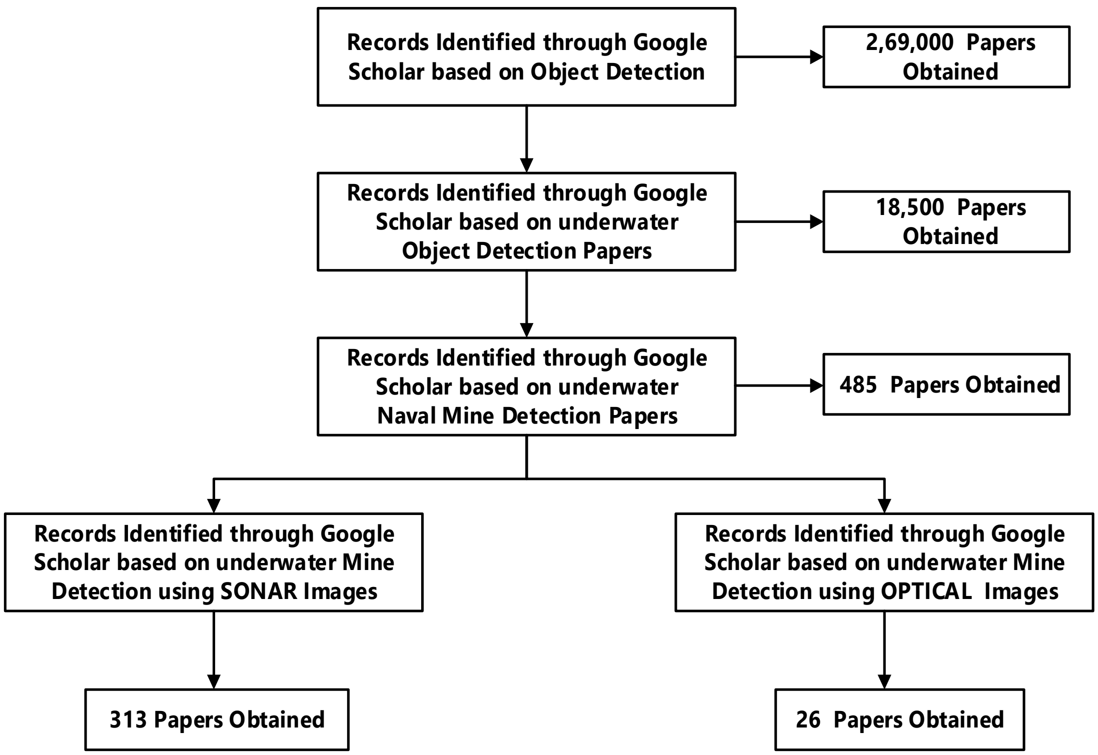


**Figure 1: The total number of publications across 4 different disciplines extending up until 2024.**

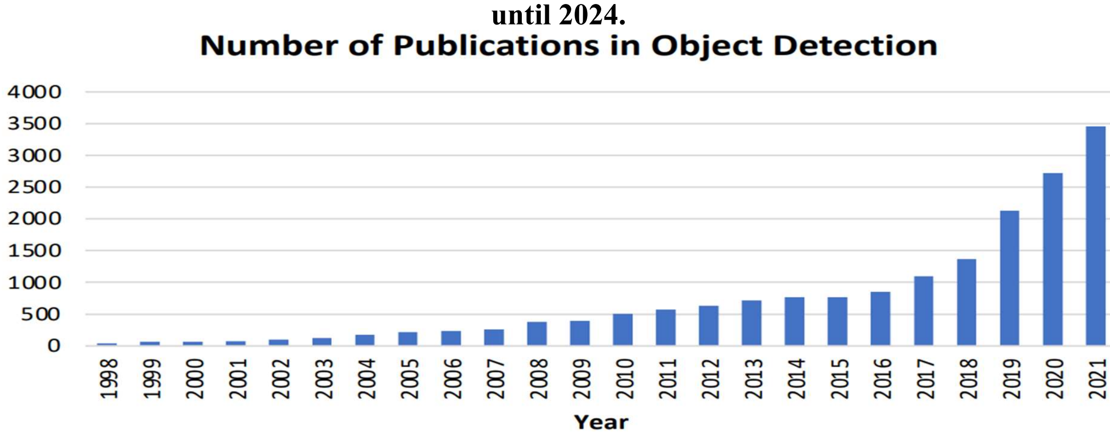


**Figure 2: Publication trend of object detection**

Fig.2 shows the growing number of publications [1] that are associated with "object detection" over the past two decades.

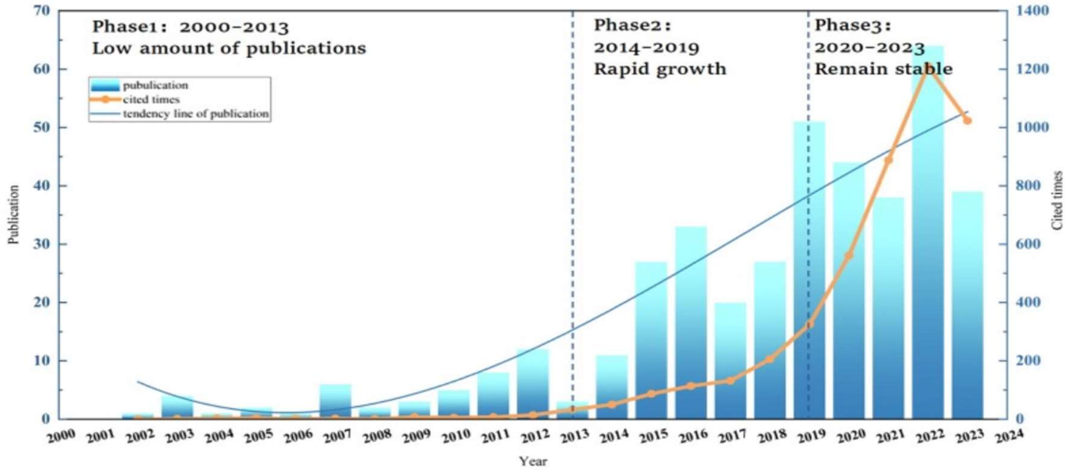


**Figure 3: Publication trend of cutting-edge technology with respect of USV**

Figure 3 illustrates the annual number of papers[2] with strong relevance to the new technology of USVs (Unmanned Surface Vessels), and shows the predicted trends for the future. It is evident that the number of annually published papers has overall steadily increased since about 2014. The number of articles in Chinese was relatively low before 2007 whose period was regarded as the initial stage of internationalisation of underwater naval mine detection in China. Additionally, Fig 3 shows that the total number of articles published has seen a curvilinear growth since 2013. Hence, 2014 can be considered a pivotal year in the globalisation of new technology in underwater mine detection research. The results show an overall increasing trend of research in underwater mines during the period from 2000 to 2023. This trend can be divided into 3 stages - (1) From the years 2000-2013, the number of publications was minimal and increased slowly, producing fewer than 15 publications; in the years 2014 - 2019, the publications were driven by special reports on underwater naval mines and the interest in considering underwater naval mines as promising auxiliary strategies has begun to increase; from (3) 2020 - present, the trend is stable as the number of publications is always higher than previous years, along with a peak at 64 papers in 2022, when the average annual publication reached 40-60 papers.

Figure 4 summarises the trend of publications [3] for studies on fish classification. The figure displays the total number of publications as well as the studies' progress during the previous 20 years. The number of publications has clearly been rising over time, but the number of studies has increased most significantly in 2016 when the first few studies combining deep learning with CV methods were published. This increase continued on a fast upward trajectory for a few years (2015–2019) following the rapid growth of DL in fish classification before slowing down.

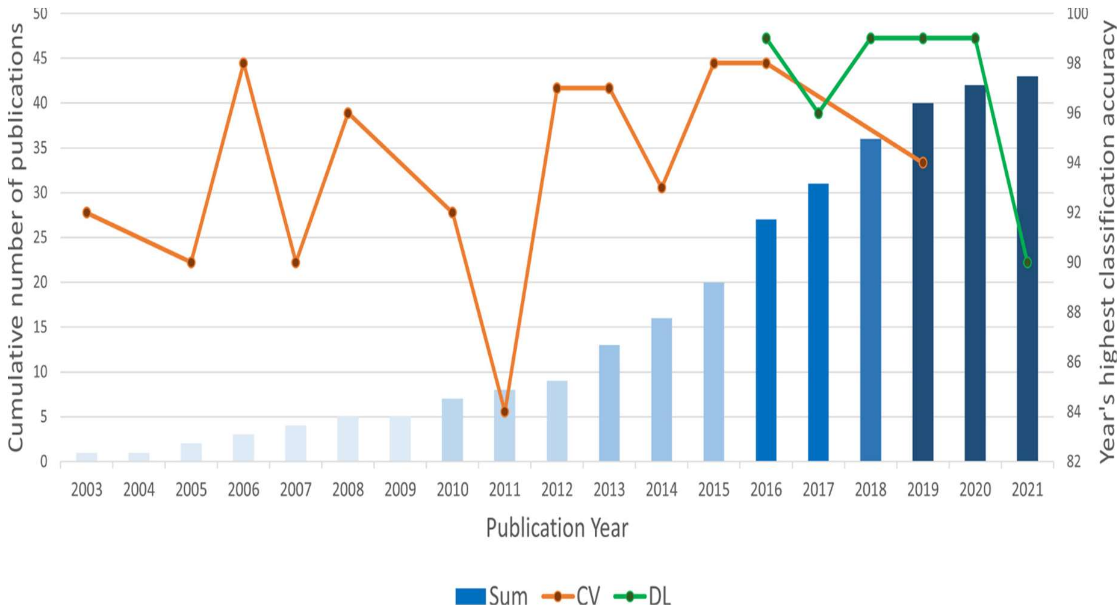


**Figure 4: Publication trend of underwater object detection**

This methodological approach ensures a thorough and unbiased review of the existing literature while adhering to best practices in academic research and publication.

2.3 Literature Review on Object Detection:

Object detection has emerged as a pivotal area in computer vision, particularly with advancements in technology that facilitate video and image analysis. Over the years, numerous methods have been proposed and developed, aiming to address challenges related to accuracy, speed, and computational efficiency

**1. Evolution of Object Detection Techniques** Early object recognition approaches heavily relied on hand-crafted features such as Scale-Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG), and Support Vector Machines (SVMs). These methods, although effective in specific scenarios, faced significant limitations due to their reliance on manually designed features and their inability to adapt dynamically to diverse datasets. Additionally, traditional architectures often incorporated imprecise and suboptimal trainable algorithms, leading to inconsistent performance across various applications.

**2.Deep Learning Integration with Object Detection** Deep learning's introduction of techniques that could automatically extract features from data transformed object detection. Convolutional Neural Networks (CNNs) emerged as a key technology in this field, allowing for notable gains in detection efficiency and accuracy. Nevertheless, a lot of early deep learning-based object recognition systems relied on additional computer vision techniques, which made them more computationally complex and hindered their ability to function in real time.

The below paragraph provides a summary of selected research papers that contribute to the field of object detection, highlighting their use in training and evaluating deep learning models. These papers represent significant advancements in the development of algorithms and methodologies, offering insights into diverse techniques and approaches employed to enhance object detection performance. By presenting key contributions and findings, this summary serves as a resource for understanding the current landscape of research in this domain.

From the launch of the YOLO (You Only Look Once) framework in 2016 to the most recent advancements in transformer-based models and semi-supervised learning in 2024, object identification has undergone substantial change. While later reviews offered insights into deep learning-based detection frameworks, difficulties, and datasets, early works, such CNN-based models and YOLO, concentrated on enhancing real-time detection and accuracy. Recent research investigates new architectures such as Vision Transformers (ViTs) and hybrid detection models that combine YOLO, SSD, and Faster R-CNN. Furthermore, the versatility of deep learning in object detection is demonstrated by specialised applications including satellite photography, underwater item recognition, and sustainable outdoor education.More recent papers delve into semi-supervised learning, spatial pyramid pooling (SPP), and transformer-based detectors, aiming to enhance accuracy, efficiency, and applicability across various domains, including security and surveillance. Overall, the field has evolved from traditional CNN-based detection to a mix of anchor-free, anchor-based, and transformer-driven approaches, addressing real-world challenges and expanding the potential of deep learning in object detection.[4]-[17]

**Object Detection:** Object detection encompasses two critical tasks: identifying the location of objects within an image (localization) and determining the category of each object (classification).

1. **Object Localization –** This technique focuses on identifying the exact position of objects in an image or video frame by defining their bounding boxes. Unlike object detection, which both identifies and classifies objects, localization aims to find where the objects are located without necessarily labeling them. For instance, in an image featuring both a cat and a dog, localization would create rectangular boxes around each animal to mark their positions. This method is widely applied in fields such as robotics (helping robots grasp objects), autonomous driving (detecting pedestrians or other vehicles), and augmented reality (overlaying virtual objects onto real-world ones).
2. **Object Classification –** This task involves categorizing the identified objects within an image or video into predefined classes. It answers the question of "what" is present in the image. For example, a classification model might recognize an image as containing a "cat," "car," or "tree" based on its trained labels. Applications of object classification are seen in areas like postal systems (identifying handwritten digits), wildlife photography (recognizing animal species), and e-commerce (classifying product types). It acts as a starting point for more intricate procedures like localisation and object detection.

The foundation was established by early object detection models that combined fundamental machine learning techniques with conventional computer vision techniques. By segmenting the process into discrete steps, these models sought to identify objects in pictures. Three main steps were present in the usual pipeline:

1. **Region Proposal**: Algorithms such as sliding windows or region proposal methods (e.g., Selective Search) were used to identify potential areas in an image that might contain objects.
2. **Feature Extraction**: Methods such as early Convolutional Neural Networks (CNNs), Scale-Invariant Feature Transform (SIFT), or Histogram of Orientated Gradients (HOG) were used to extract features from these suggested locations.
3. **Classification and Localisation**: To identify the objects and fine-tune their bounding boxes, the retrieved features were subsequently fed into classifiers (such as CNN-based classifiers or Support Vector Machine classifiers). The application of Non-Maximum Suppression (NMS) eliminated duplicate detections.

Deep learning was incorporated into the process by one of the first models, R-CNN (Regions with CNN features), which greatly increased detection accuracy. These early models, however, processed each region separately and required a lot of computing power. As a result of this restriction, more effective techniques like YOLO, Fast R-CNN, and Faster R-CNN were created. Typical classifiers and localisers in conventional object detection models are shown in Figures 5 and 6.

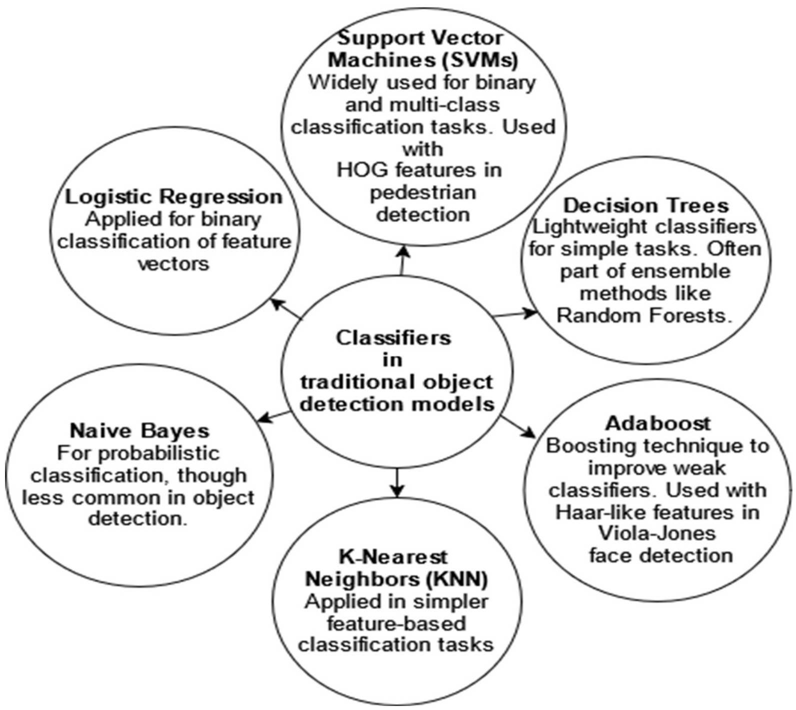


**Figure 5: Commonly used classifiers in traditional object detection models**

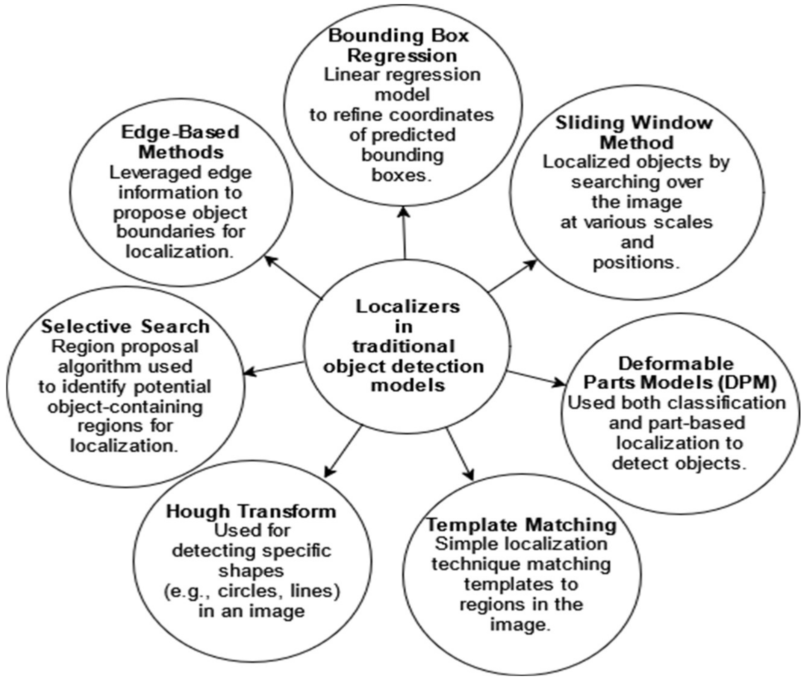


**Figure 6: Commonly used Localizers in traditional object detection models.**

These techniques formed the foundation of traditional object detection models before deep learning advancements simplified and unified classification and localization processes. Figure 7 and 8 illustrates commonly used classifiers and localizers in commonly used in deep learning-based object detection models.

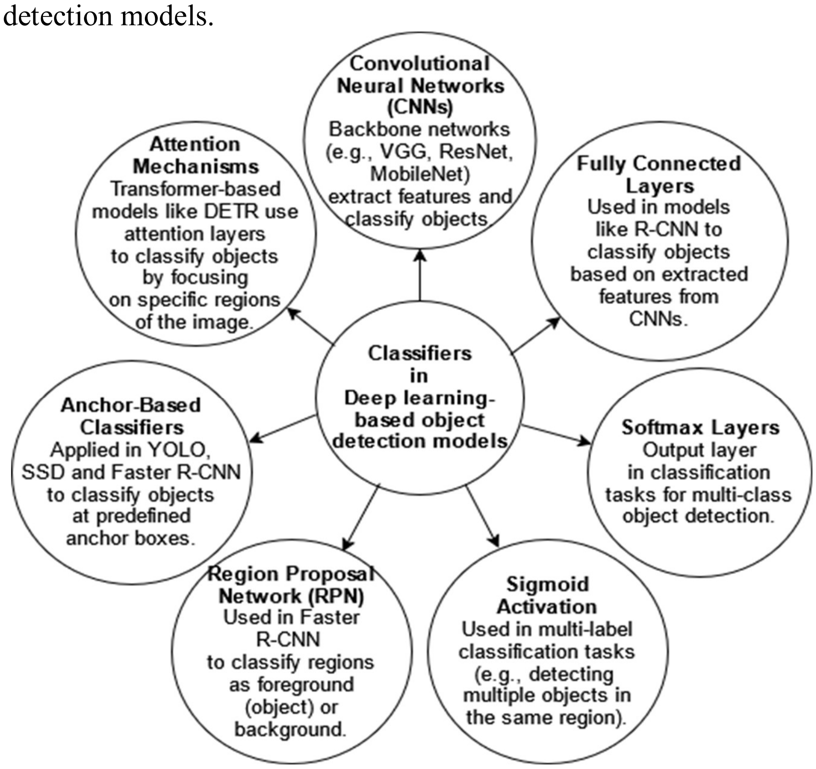


**Figure 7: Classifiers in deep learning-based object detection models.**

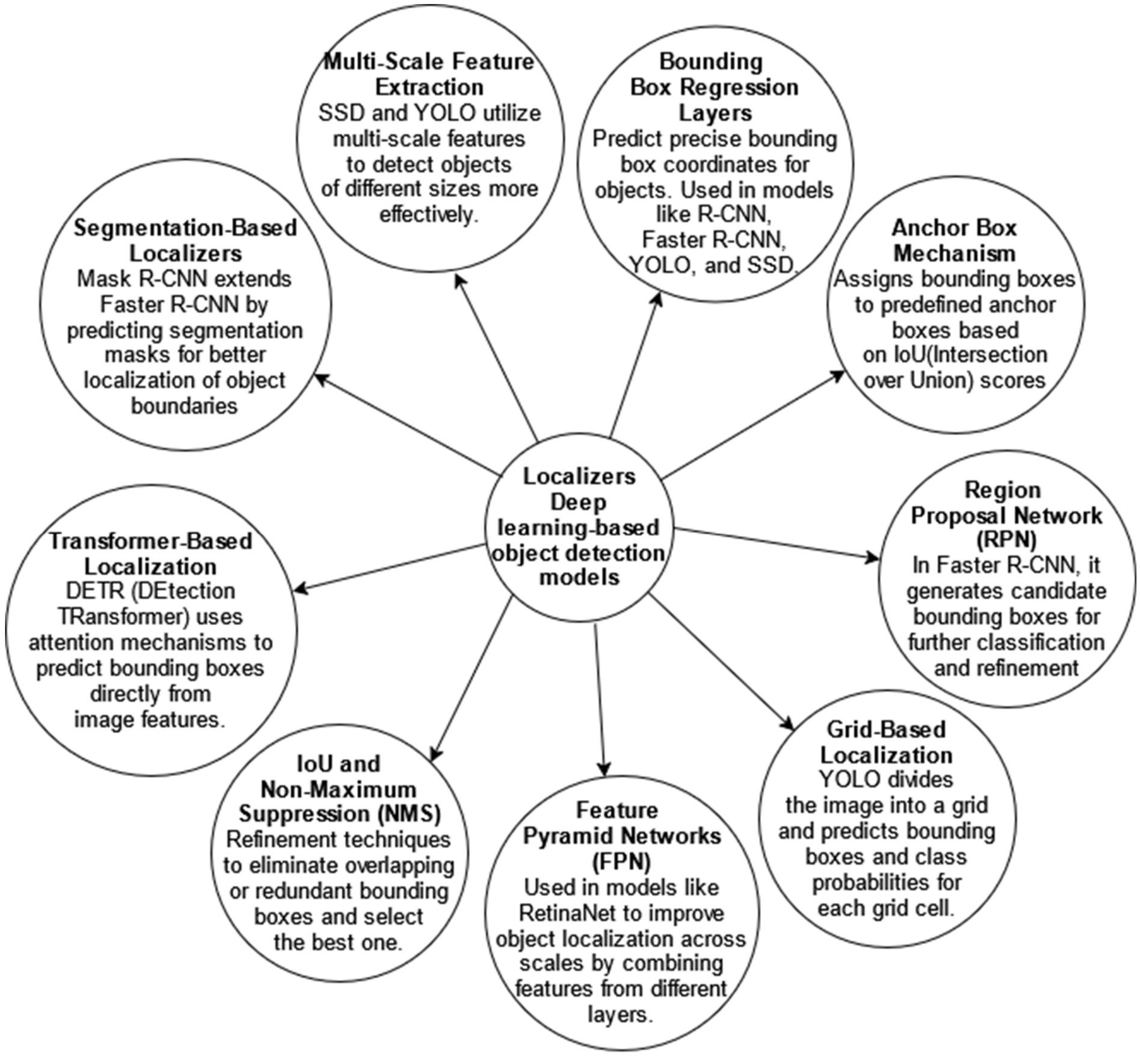


Figure 8: Localizers in deep learning-based object detection models

Deep learning models unify classification and localization into end-to-end frameworks, using these techniques to achieve state-of-the-art performance in object detection tasks.

## Object Detection Models

Traditional machine learning models utilize mathematical and statistical techniques to process data and generate predictions. These models, including logistic regression, decision trees, support vector machines, k-nearest neighbors, and linear regression, are particularly effective for analyzing structured data. Unlike deep learning models, which learn directly from raw data, traditional models depend on manually extracted features. They are well-suited for smaller datasets and tasks such as classification, regression, and clustering due to their simplicity, interpretability, and lower computational demands. Despite advancements in deep learning, these models remain widely used across various domains for their reliability and effectiveness. Figure 9 shows a thorough comparison of various models.

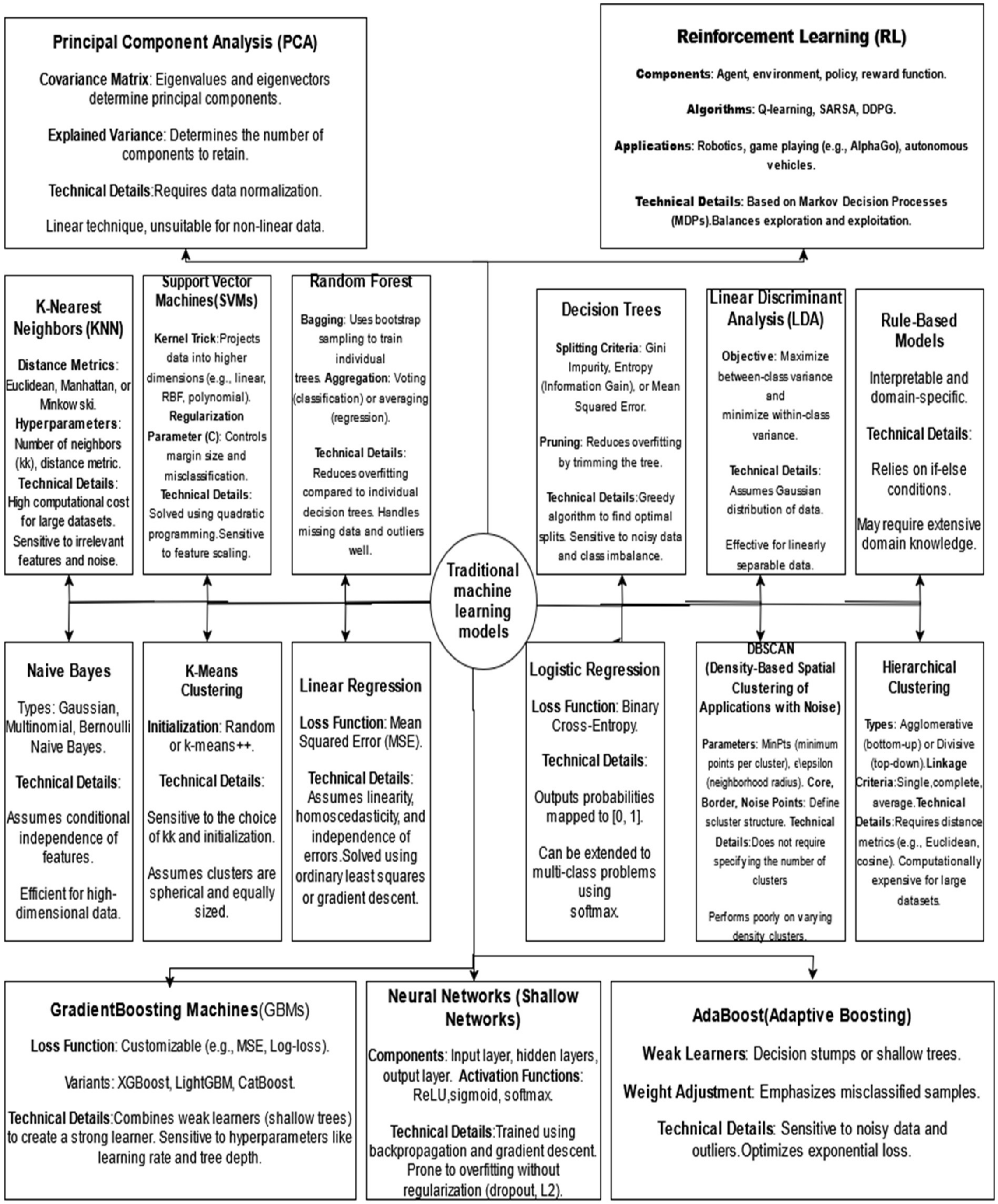


**Figure 9: Traditional machine learning models with descriptions and technical details.**

Deep learning models are advanced machine learning methods that use artificial neural networks and are modelled after the structure and operation of the human brain. These models are very useful for complicated tasks like speech creation, image recognition, and natural language processing since they automatically acquire hierarchical features from raw data. Deep learning, which uses architectures like convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers to learn directly from the data, eliminates the need for manual feature extraction, in contrast to classical machine learning. Deep learning has revolutionised several sectors by identifying complex patterns and producing state-of-the-art performance, despite the fact that it necessitates massive datasets and substantial processing capacity. Some of the most popular deep learning models and their technical attributes are shown in Figure 10.

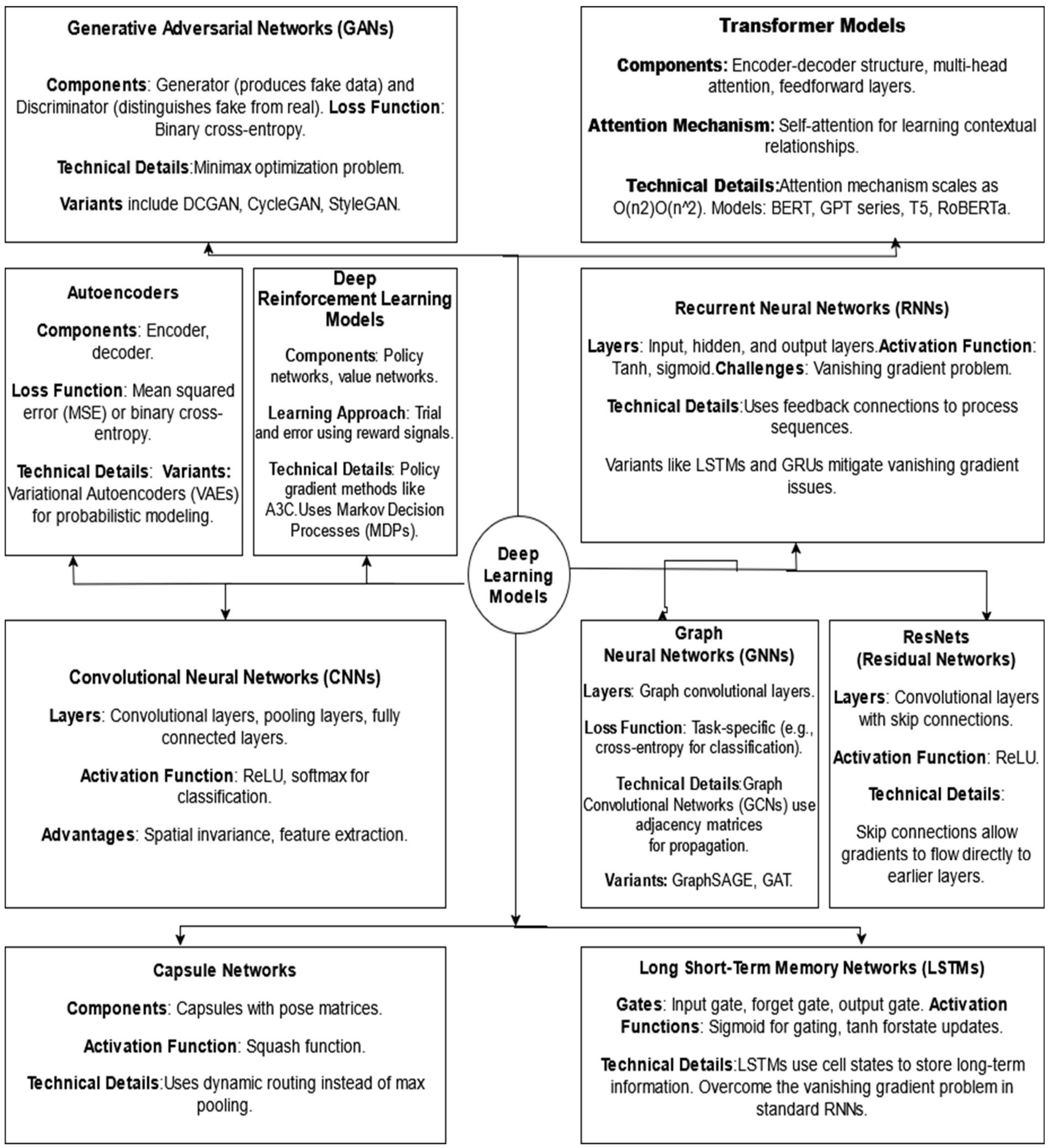


**Figure 10: Deep learning models with descriptions and technical details**

## 2.4 Literature Review on Object Detection through Semantic Segmentation

Semantic segmentation is a computer vision technique that labels each pixel in an image, dividing it into regions corresponding to different objects or classes. Unlike object detection, it provides detailed, pixel-level understanding, helping machines interpret visual data. This method is used in areas like autonomous driving, medical imaging, and scene understanding, with advancements in deep learning models like CNNs, U-Net, and DeepLab improving accuracy and efficiency.

Semantic segmentation faces several challenges, including occlusions, overlapping objects, and the difficulty of obtaining large annotated datasets for training. Real-time processing is also a critical issue, especially in applications like autonomous driving, where quick and accurate segmentation is necessary to ensure safety.

The below paragraph summarizes selected research papers on semantic segmentation, highlighting key advancements in deep learning-based segmentation techniques. Fully Convolutional Networks (FCNs), introduced in 2015, marked a breakthrough by enabling end-to-end learning for semantic segmentation without complex post-processing. U-Net, also introduced in 2015, became a standard for biomedical image segmentation, excelling in neuron and cell segmentation. DCAN (2017) proposed a deep contour-aware network for improved object instance segmentation in histology images, while FISA (2017) enhanced image retrieval using local features. Several review papers, including a 2018 study, provided comprehensive overviews of deep learning approaches, datasets, and challenges in semantic segmentation. A 2019 study categorized methods into traditional and deep learning-based techniques, while a 2020 survey discussed the evolution of CNN-based segmentation models, detailing their architectures and hyperparameter tuning. A 2021 study explored semantic segmentation methods for scene understanding, covering models like DeepLab and FCN-CRF. More recent advancements focus on domain-specific applications, such as Feature Pyramid U-Net with Attention (2022), which improved forward-looking sonar image segmentation, and BHP-UNet (2023), which enhanced side-scan sonar underwater target segmentation, demonstrating superior performance over conventional models. These studies collectively illustrate the progress in semantic segmentation, offering insights into evolving architectures, dataset utilization, and application-driven improvements.[18]-[28]

## 2.5. Literature Review on Underwater Object Detection

Advancements in underwater object detection have significantly benefited from deep learning techniques, pushing the boundaries of understanding the marine environment. Traditional state-of-the-art (SOTA) methods face challenges, prompting a need for improved models. A study highlighted the importance of pretraining models with ImageNet data to enhance performance. It showed that two-stage detectors outperform single-stage ones in terms of Accuracy, Intersection over Union (IoU), and Floating Point Operations Per Second (FLOPS). Notably, the DetNas20 + FRCNN architecture achieved an 80% Average Precision (AP) on the Brackish dataset. The study also suggests incorporating enhancement and reconstruction techniques and exploring semi-supervised learning for better model efficiency, using datasets like URPC2019 and Brackish for evaluation.

Recent advancements in underwater object detection and recognition have leveraged deep learning techniques to improve accuracy and efficiency. Fast R-CNN and Faster R-CNN models have demonstrated high precision in fish detection, seagrass identification, and underwater biodiversity monitoring. Surveys highlight the growing role of deep learning in seabed imagery analysis and marine species classification. Improved YOLO models with transfer learning and multi-scale attentional feature fusion have further enhanced underwater object detection, balancing accuracy and speed. Novel techniques such as adversarial occlusion networks, convolutional autoencoders, and synthetic datasets have improved robustness and generalization. Additionally, unsupervised methods, including adaptive uncertainty distribution and conditional variational autoencoders, have been explored for underwater image enhancement. Recent benchmarks and datasets, such as DUO, address dataset limitations, promoting the development of high-accuracy models. These advancements contribute to applications in marine ecology, hydropower monitoring, underwater robotics, and maritime security [29] to[48].

This collection of research papers from 2022-2023 explores various deep learning-based approaches for underwater object detection, classification, and recognition. Key topics include sonar-based vessel classification for shoreline surveillance, underwater target detection in turbid environments, and fish detection using CNNs and YOLO architectures. Several studies focus on enhancing underwater image quality with CNN-based defogging and segmentation techniques, while others investigate acoustic signal classification using neural networks. Notable advancements include the use of graph convolutional networks for crack detection, transfer learning for sonar data classification, and residual CNNs for ship recognition. These works highlight the growing role of AI in underwater sensing, emphasizing improved accuracy, dataset augmentation, and real-time processing capabilities [49]-[68].

This collection of recent research papers (2023-2024) focuses on advancements in underwater object detection and image enhancement. Key topics include underwater crack detection on concrete dam surfaces using robotic imaging and digital processing, improved Faster R-CNN models for detecting marine species, and a novel Boosting R-CNN approach that enhances detection accuracy through uncertainty modeling and hard example mining. Additionally, a review highlights the challenges of deep learning in marine object detection due to data scarcity. Lastly, UICE-MIRNet, an underwater image enhancement method, is introduced to improve object visibility, particularly for small and dense targets, demonstrating superior performance compared to existing techniques [69]-[73].

## 2.6. Literature Review on Underwater Naval Mine Detection

This section provides a summary of selected research papers focused on underwater naval mine detection using sonar images. This collection of research papers (2003-2020) explores various techniques for underwater mine detection using sidescan sonar images. Early works introduced the Co-operating Statistical Snake (CSS) model for highlight-shadow segmentation and symbolic pattern analysis for real-time detection. Later studies incorporated neural networks and unsupervised morphological operators for improved classification, optimizing for computational efficiency. More recent advancements focus on Automated Machine Learning (AutoML) for generalized underwater object detection, achieving high precision in sonar-based docking station identification. Additionally, data mining and machine learning approaches have demonstrated high accuracy in discriminating mine-like objects, highlighting the evolution toward more robust and efficient detection systems. [74]-[79]

Recent research (2021-2024) on underwater mine detection using sonar imagery has emphasized automation through CAD, CAC, and ATR systems to reduce operator workload. Deep learning models, such as Faster R-CNN, and segmentation networks like DeepLabV3 and U-Net++, have shown high accuracy, with transfer learning and data augmentation further improving detection performance. Studies on forward-looking sonar analyze object intensity profiles for classification, while machine learning algorithms, including SVM, KNN, and ensemble methods, effectively differentiate mines from rocks. A 2024 study introduces a novel approach using sonar signals recorded at multiple angles to predict underwater mines and rocks, enhancing naval defense systems with improved classification precision. Advancements in automated mine detection using side-scan sonar continue to enhance safety and reduce false negatives, making detection systems more reliable and efficient [80]-[85.

This section provides a summary of selected research papers focused on underwater naval mine detection using optical images. Recent studies explore advanced image processing and machine learning techniques to enhance detection accuracy in complex underwater environments. Methods such as deep learning-based object detection, feature extraction, and classification have been applied to optical imagery to improve identification and differentiation of mine-like objects. Research also highlights challenges such as low visibility, noise, and varying lighting conditions, with solutions including image enhancement techniques and adaptive algorithms. These advancements contribute to the development of more efficient and reliable underwater mine detection systems. The Summary of selected research papers focused on Underwater Naval Mine Detection using optical images shown in Table 1.

Table 1 Summary of selected research papers focused on Underwater Naval Mine Detection using optical images

| Sl. No | Year and Title | Description |
|---|---|---|
| 1 | 2013-Sensitive test for sea mine identification based on polarization-aided image processing [87] | Once a mine is detected, the identification process begins. We focus on the asymmetric segmented phase-only filter to assess recognition rates, as it allows for more reference images in its design. However, its performance remains suboptimal, producing low-quality images. To address this, we propose using a single-wavelength polarimetric camera for denoising, enhancing image clarity and depth perception. Our results, obtained through in situ polarization imaging of a target in a milk-water mixture, demonstrate improved detection rates and reduced false alarms. |
| 2 | 2020-Underwater Mine Detection using Image Processing [88] | The image classification model employs the FRCNN (Fast Region Convolutional Neural Network) algorithm to categorize objects as either mines or non-mines. A cloud platform monitors the mine, and any detected changes are promptly reflected in the Android application. |
| 3 | 2020-Underwater Mines Detection using Neural Network [89] | This paper utilizes the Mask RCNN model for mine detection, with the ResNet-50 architecture employed to implement the Mask RCNN. The process includes image pre-processing followed by feature extraction using FPN in the Mask RCNN. Upon successful implementation, the system demonstrated satisfactory accuracy in detecting |

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| | | mines. This approach could be expanded to identify other marine objects using the Faster RCNN model. |
| 4 | 2021-Detection and Feature Extraction of Naval Mines Using CNN Architecture [90] | This study present a method which can auto label the image dataset and then predict if the image consists of naval mines or not. A comparative study is carried out using 4 different CNN architectures. |
| 5 | 2021-Underwater Mine Detection Using Histogram of oriented gradients and Canny Edge Detector [91] | In this paper feature extraction methods- Histogram of oriented gradients and edge-based feature extraction are used. The data undergoes preprocessing- resizing and converting to grayscale images- after which the feature extraction method is applied. To classify whether the image contains a mine or not, template matching and classification methods feature vectors are used. The method was found to achieve high accuracy in mine detection. |
| 6 | 2022-Sea Mine Detection Framework Using YOLO, SSD and EfficientDet Deep Learning Models [92] | This study focuses on detecting floating and underwater sea mines using images captured by cameras on drones, submarines, ships, and boats. Due to the limited availability of sea mine images, data augmentation and synthetic image generation techniques were employed, creating separate datasets for floating and underwater mines. Three deep learning models—YOLOv5, SSD, and EfficientDet—were trained and evaluated, with YOLOv5 and SSD used for floating mines and YOLOv5 and EfficientDet for underwater mines. The developed system demonstrated high accuracy in detecting both floating and anchored mines. Additionally, tests on portable computing devices like Raspberry Pi showed the feasibility of real-time implementation, with frame processing times improving when high-performance cameras are used. |
| 7 | 2023-Marine Mine Detection Using Deep Learning. [93] | This study explores the detection of floating and underwater marine mines using images captured by cameras on drones, submarines, ships, and boats. Given the limited availability of image datasets, additional images were sourced online and enhanced through data augmentation and synthetic image generation by overlaying different mine types on water backgrounds. Two distinct datasets were created for floating and underwater mines. The detection models were trained and evaluated using YOLOv5, SSD, and EfficientDet, with YOLOv5 and SSD applied to floating mines and YOLOv5 and EfficientDet to underwater mines. Additionally, the models were tested on an IoT device using a Raspberry Pi 4 and an RPi camera. |
| 8 | 2023-System based on autonomous aerial and maritime surface vehicles to identify sea mines and support the intervention | The overall objective takes into consideration that the involvement of specialized forces in neutralizing explosive devices entails a series of intricate tasks. These tasks include searching, detecting, identifying, assessing the location, safely neutralizing or destroying the devices, and |

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|---|---|---|
| | team in the neutralization mission [94] | recovering and disposing of improvised explosive devices or munitions. |
| 9 | 2023-Machine Learning based Underwater Mine Detection [95] | This study proposes utilizing the XGBoost algorithm to develop a predictive system for differentiating between rocks and mines. The model's accuracy is assessed and compared with existing approaches to evaluate its effectiveness in classification. |
| 10 | 2023-Classification of Underwater Mines with Convolutional Neural Networks [96] | This methodology involves the CNN's training process on diverse datasets containing images or features associated with different mine types. The network learns to automatically extract hierarchical and spatial features, enabling it to discern subtle patterns indicative of various mine classes. |
| 11 | 2023-Synthetic Underwater Naval Mine Dataset Generation and Naval Mine Detection Using Custom CNN Model-Deep Neural Networks [97] | The dataset consists of fourteen different types of underwater mines, each containing 150 images. The Adam optimizer is employed during training, and the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique is applied for preprocessing. A custom CNN model is trained using both the RVUMR-14 dataset and the CIFAR-10 dataset, with an 80:20 split for training and validation. The model achieved an accuracy rate of 91%. The effectiveness of the RVUMR-14 dataset is validated through a comparison with the benchmarked CIFAR-10 dataset, where RVUMR-14 outperformed CIFAR-10 with a 91% accuracy, compared to CIFAR-10's 76%. |
| 12 | 2023-Hybrid Deep Learning Model for Detecting Underwater Naval Mines [98] | Among the models employed were CNN (Convolutional Neural Network), YOLOv5, VGG-19, and a hybrid fusion of CNN-VGG-19 and CNN-MobileNet. Remarkably, CNN showcased outstanding performance, achieving an impressive accuracy rate of 98%. Additionally, YOLOv5 demonstrated robust performance, closely trailing behind with an accuracy score of 97%.Surpassing them all, the hybrid models, specifically the CNN-VGG19 and CNN-MobileNet fusion, showcased the highest accuracy, reaching an outstanding 99%. |

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