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TOPICAL REVIEW

How High-Tech Solutions Support the Fight Against IUU and Ghost Fishing: A Review of Innovative Approaches, Methods, and Trends

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ABSTRACT Illegal, Unreported, and Unregulated fishing is a major threat to human food supply and marine ecosystem health. Not only is it a cause of significant economic loss but also its effects have serious long-term environmental implications, such as overfishing and ocean pollution. The beginning of the fight against this problem dates since the early 2000s. From that time, a number of approaches and methods have been developed and reported. A key role in this topic is played by machine learning algorithms which exploit data provided by classical and high-tech sensors, devices and systems such as for example: CCTV, on-board cameras placed on autonomous vehicles, Global Positioning Systems, radars, Automatic Identification Systems, Vessel Monitoring Systems, or Coastal Surveillance Systems. The main objective of this paper is to provide the reader with knowledge about the scale of this phenomenon, methods to tackle the issue, and the current state of research on the subject. This has been achieved through a review of existing approaches that deal with these harmful phenomena by using dedicated artificial intelligence and machine learning tools, as well as the accompanying equipment and devices. In addition, flaws and gaps in current methods, and future directions are disscussed.

INDEX TERMS Artificial intelligence, autonomous systems, boat tracking, ghost fishing, intelligent vehicles, IUU, machine learning.

ACRONYMS

AAV – Autonomous Aerial Vehicle.
AI – Artificial Intelligence.
AIS – Automatic Identification System.
ALDFG – Abandoned, Lost or otherwise Discarded Fishing Gear.
ANN – Artificial Neural Network.
ASV – Autonomous Surface Vehicle.
AUV – Autonomous Unmanned Vehicle.
Buscamos – The proper name of an autonomous boat developed by the DAyRA (División de Automatizacióny Robótica Autónoma) group at the Technical University of Cartagena (UPCT).
CCTV – Closed Circuit TeleVision.
CE – Centroid Encoder.
CNN – Convolutional Neural Network.
COCO – Common Objects in COntext, benchmark dataset for deep learning.
CSR – Coastal Surveillance Radar.
CSS – Coastal Surveillance System.
DBSCAN – Density-Based Spatial Clustering of Applications with Noise.
DL – Deep Learning.
DNN – Deep Neural Network.
DR – Dimensional Reduction.
DTW – Dynamic Time Warping.
FAST – Features from Accelerated Segment Test.
FCN – Fully Convolutional Network.
FLS – Forward Looking Sonar.

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FMC – Fisheries Monitoring Center.
GAN – Generative Adversarial Network.
GMM – Gaussian Mixture Model.
GNN – Global Nearest Neighbour.
GPS – Global Positioning System.
GvMMM – Gaussian-Von Mises Mixture Model.
IUU – Illegal, Unreported and Unregulated.
K-NN – K-Nearest Neighbours.
mAP – Mean Average Precision.
ML – Machine Learning.
MLP – Multilayer Perceptron.
MRF – Multiple Receptive Field.
MSER – Maximally Stable External Regions.
OCR – Optical Character Recognition.
R-CNN – Region Based Convolutional Neural Network.
ResNet – Residual Neural Network.
RF – Random Forest.
ROI – Region of Interest.
RUSBoost – Random Undersampling Boosting.
SAR – Synthetic Aperture Radar.
SIFT – Scale-Invariant Feature Transform.
SSD – Single Shot MultiBox Detector.
SVM – Support Vector Machine.
UAV – Unmanned Aerial Vehicle.
U-Net – CNN architecture that was developed for biomedical image segmentation.
USV – Unmanned Surface Vehicle.
UUV – Unmanned Underwater Vehicle.
VMS – Vessel Monitoring System.
YOLO – You Only Look Once, convolutional neural network architecture.

I. INTRODUCTION

Because of investment and logistical difficulties, fishing is a business of slow technological progress. Managing fisheries to achieve the expected profits on the one hand, and to ensure long-term and sustainable development of fisheries while caring for the surrounding environment on the other is a complex, difficult, and challenging task. Due to significant global population growth, the demand for fish protein continues to increase, but the current number of global fish stocks is running low and is unable to provide the maximum sustainable yield [1], [2], [3], [4]. In the future, ensuring food security could be a major problem [5], [6], [7]. Fishing should not be treated as an ''ordinary'' business, because, if not managed properly and without adequate oversight by dedicated government and intergovernmental bodies, depletion of fish stocks can become irreversible. The sources of the problems go beyond the pure management layer, as they include, for instance, the treatment of fishing communities, who are often disenfranchised, poorly organized and lacking a voice in the policy process [8]. This leads to the search for alternative ways of earning money, often illegal and not complying with the accepted rules, but cheaper and quicker to profit. Non-compliant activities increase long-term environmental and economic risks.

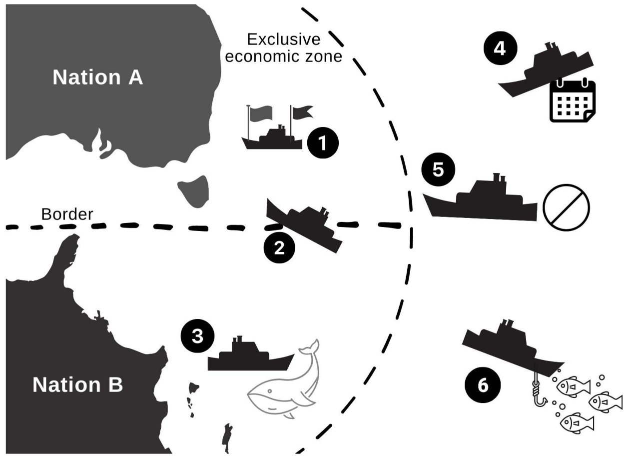

FIGURE 1. IUU fishing examples (based on [10]). 1. Vessel with dual or false flags; 2. Unlicensed border hopping; 3. Fishing non-permitted species; 4. Fishing out of season; 5. Fishing in prohibited area or without license; 6. Fishing with illegal gear or above quota.

The above problems often lead to the so called Illegal, Unreported and Unregulated fishing (IUU fishing). The problem was first described and presented in the report by the Food and Agriculture Organization of the United Nations in 2001 [9]. Figure 1 shows typical examples of behaviour characteristic for IUU fishing. They include, but are not limited to, having a double or false flagged vessel, unlicensed border crossing, fishing with illegal gear, fishing out of season, fishing above quota, and fishing in prohibited areas or without the license.

To fully understand what IUU fishing means, it is necessary to look at its definition. Fishing is *illegal* when it takes place in the territorial waters of a country without a permit, or in a manner that violates laws, regulations, and restrictions on environmental protection and regional fisheries policy. *Unreported* means that it has not been duly reported to the relevant legal authority in charge of fisheries regulation. Whereas, *unregulated* is the term used to describe activities carried out in the area of the relevant regional fisheries management organisation by vessels without an authorised registration to fish or engaged in improper fishing activities.

IUU fishing is a major threat to human food supply [11], marine ecosystem health, and geopolitical stability. It has a major impact on the economy. These days, it is estimated that IUU fishing accounts for approximately 14–33% of the global catch. Annually, illegal fishing generates 15.5 billion USD to 36.4 billion USD in illicit profits [12]. Moreover, it is often connected to trans-national crimes, including human rights abuse, bonded labour, tax evasion, piracy, drug, arms, and human trafficking. IUU fishing also exacerbates the effect of climate change on ocean resources. One of the consequences of increased IUU levels is ghost fishing. Ghost fishing is a term that refers to Abandoned, Lost or otherwise Discarded Fishing Gear (ALDFG) that is still in the water and is causing death of aquatic organisms without human control.

The accidental loss of some fishing gear is unavoidable, for example due to extreme weather conditions during fishing.

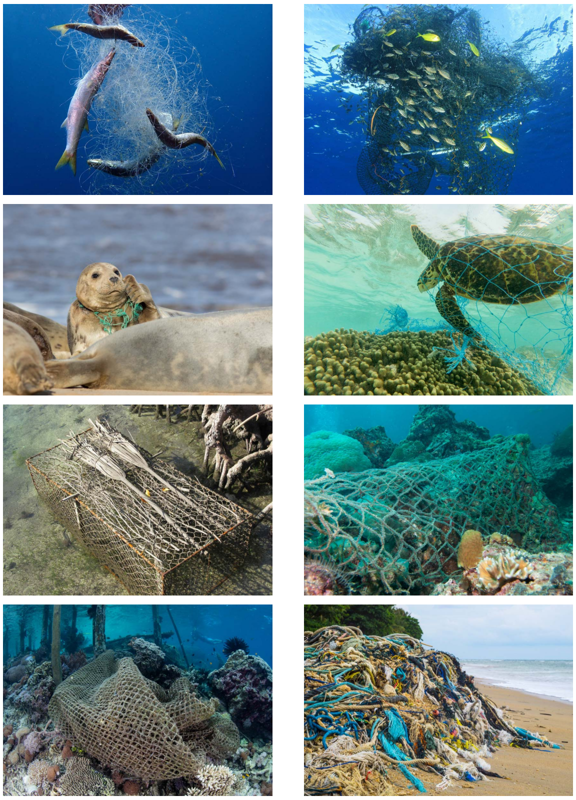

FIGURE 2. **Examples of ghost nets. The first and second rows show animals such as fish and turtles entangled in nets. The third and fourth rows show an abandoned trap, nets entwining coral reefs, and the beach being polluted with fishing nets.**

Nevertheless, part of the gear is discarded on purpose and part is abandoned when it is possible to recover it, due to the pressure on fishermen to abandon gear as a form of avoiding responsibility by disposing of evidence of illegal activity (e.g. illegal fishing or illegal gear) [13]. Estimated 640,000 tonnes of fishing gear are left in oceans each year, thus resulting in the so-called ghost gear [14]. The World Conservation Organization estimates that entanglement in fishing gear causes the deaths of at least 136,000 seals, sea lions, and large whales each year. An inestimable number of birds, turtles, fish, and other species are injured and killed as well. Moreover, in parallel to causing animal deaths, nets made of synthetic materials contribute to the pollution of the oceans. In a business-as-usual scenario, the ocean is expected to contain more plastics than fish (by weight) by 2050 [15]. Figure 2 shows examples of abandoned or lost fishing gear that entangles wildlife, destroys coral reefs or pollutes the water.

IUU fishing is not only a cause of significant economic loss but its effects have serious long-term environmental implications, such as overfishing and ocean pollution.

The regulations established by fishery management authorities balance the exploitation with the natural process of stock recovery [9], [16], [17]. The implementation of permanent or seasonal fishing prohibitions is related to the presence of various protected fish species or the need to restrict fishing to ensure population growth during hunting seasons. Fortunately, the disadvantage of these regulations is that they are associated with lower financial income for fishers and fishing companies. However, there is a solution to this drawback. Many nations can recover their fisheries while avoiding substantial short-term reduction costs by sharply addressing IUU fishing [18]. This can accelerate fishery recovery, often at little or no cost to local economies or food provision.

The fight against IUU fishing has been an ongoing one. The beginnings of taking the problem seriously can be traced back to 2001, when the International Plan of Action (IPOA) on IUU Fishing was established [9]. An important milestone in this fight was the formation in 2016, of Global Fishing Watch (GFW) [19], [20] by Google in partnership with Oceana and SkyTruth. With the progress of technology, more and more effective tools are developed every year to fight IUU fishing.

Unfortunately, fishermen operating illegally are constantly improving their ways of violating and circumventing laws and restrictions. There is a never-ending race to see who will be more effective, in the short and long term. That is why in recent years an increasing use of Artificial Intelligence (AI) and Machine Learning (ML) tools engaged in the battle against IUU fishing has been witnessed. Many researchers [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33] have shown that such tools, when combined with classic and modern devices such as CCTV, drones, autonomous vehicles, etc., can be extremely effective and can make a significant contribution to reducing its scale and consequences. The mentioned research works are described in more detail later in Section 3 of this paper.

The main objective of this paper is to review the existing approaches to deal with these harmful phenomena using dedicated AI and ML tools as well as the accompanying equipment and devices. The paper will indicate different approaches to the problem, describe the technologies used, and provide a description of IUU fishing and its consequences. All this, will allow the reader to gain an understanding of the scale of this phenomenon, methods to tackle it, and the current state of research on the subject. Finally, on the basis of the collected knowledge, the most important directions of further development will be presented, and the current difficulties occurring in the technological fight against IUU will be indicated.

Data was collected from the following academic digital databases: ArXiv, IEEE, Google Scholar, Scopus. All studies written in English, regardless of the publication status (peer-reviewed or published articles), were included in this review. Studies were identified by the keywords: IUU, ghost fishing, boat tracking, machine learning, artificial intelligence, autonomous systems. Then, each study was screened for content relevance. A total of 17 articles were collected and discussed.

The remainder of this paper is organized as follows. In Section II the basics of equipment, systems and algorithms used for detecting IUU fishing are described. Section III presents selected applications using modern methods dealing with the phenomenon and its consequences. The discussion is presented in Section IV, while the last Section V concludes the paper.

II. DESCRIPTION OF EQUIPMENT, SYSTEMS AND ALGORITHMS USED FOR DETECTING IUU FISHING

To be able to achieve the desired goal, a skillful combination of sensors, devices, supporting systems, data, and algorithms, and an appropriate analysis of their results is essential. This section provides an overview of elements used as a data source in systems described in Section 3. The systems used to prevent IUU fishing are typically based on satellite, visual (CCTV, or on-board cameras placed on autonomous vehicles), and/or radar systems which provide a great amount of data. At the same time, hundreds of thousands of vessels are transmitting their positions, speeds, and other information around the world. The video systems deliver thousands of hours of footage. The amount of data delivered is almost uncountable, which is referred to as the so-called Big Data problem. A real time analysis of the data with acceptable speed is impossible for humans without supporting systems. There are many advanced algorithms of data processing and analysis for example AI based algorithms that may be used to process data efficiently and effectively. AI is ideally suited for finding patterns in the maze of data. Such algorithms can be useful, for instance, in detecting illegal activities based on satellite data. Combining them with autonomous systems provides a new capability to detect IUU fishing vessels and ghost nets without human intervention.

This section covers three issues. The first one describes the basic types of autonomous units that provide installation platforms for sensors. The second one is about surveillance systems that provide data ranging from location time series to images. The third one deals with algorithms that process large amounts of data obtained with the aforementioned sensors and systems.

A. EQUIPMENT

Unmanned Aerial Vehicles (UAVs) are small unmanned aircrafts commonly known as drones (Figure 3), which are capable of performing tasks under remote control or autonomously. Highly advanced crafts which do not require an operator are called Autonomous Aerial Vehicles (AAVs). They have recently become advanced and affordable, making a large-scale impact on various business and scientific activities. Drones are used for a variety of purposes, for example in coastline patrolling tasks [34], [35] or detecting litter on beaches [36], and their utility can be easily extended to IUU fishing prevention, for example, they can help to quickly reach the locations of IUU fishing or illegal or abandoned fishing gear.

Unmanned Surface Vehicles (USVs) are generally small surface vessels equipped with precision sensors, which are able to make autonomous decisions and move without human

FIGURE 3. UAV example, Japanese P8 maritime patrol aircraft for security and surveillance [37].

FIGURE 4. USV AutoNaut [38].

crew (Figures 4 and 5). Compared to conventional manned vessels, they are able to carry out missions for longer periods of time without endangering personnel. USVs are often equipped with solar panels to significantly increase their operational range while also using renewable energy sources. The development of autonomous systems of such vessels makes them more and more used. USVs are used, for example, for detecting and tracking the movement of ships within a defined area, or on a designated patrol route. Current solutions are rather in the experimental and testing phase. The literature also recognises the notation Autonomous Surface Vehicle (ASV) to highlight autonomous capabilities of the vehicle.

Unmanned Underwater Vehicles (UUV) are typically small, manoeuvrable, unmanned underwater robots (Figure 6). Fully autonomous vessels are sometimes referred to as Autonomous Underwater Vehicles (AUVs) to underline the absence of human operators. Sometimes UUVs are controlled remotely or their activities are constantly supervised by a human operator. Such vessels are most commonly used for monitoring the seabed. They are equipped with algorithms for detecting and hence avoiding abandoned or lost fishing gear. Such algorithms can be easily adopted for preventing ghost fishing.

FIGURE 5. USV Buscamos [39].

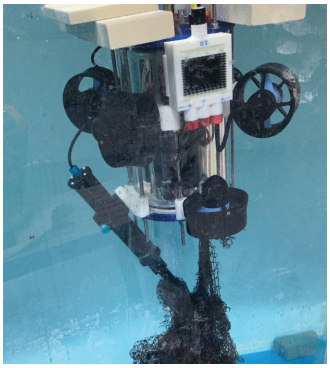

FIGURE 6. UUV example [28].

B. SUPPORTING SYSTEMS

Automatic Identification System (AIS) is a system that provides automatic communication and data transfer between ships for collision avoidance and identification purposes. Such systems were developed and implemented in the early 2000's. The AIS enables continuous data transmission on a vessel's identity, position, speed and course, along with other relevant information to all other AIS equipped vessels within range. According to the International Maritime Organization guidelines - Resolution A.917(22) [40], AIS should be active whenever the ship is underway or at anchor. The detection of a vessel with AIS off is the first indication of possible illegal activity.

Vessel Monitoring System (VMS) is a system that monitors the location and movement of fishing vessels. It operates on the basis of satellite surveillance - the Global Positioning System (GPS) - and on-board transceivers. Unlike AIS, VMS is restricted to government regulators or other fisheries authorities. VMS is integrated with land-based national centres - Fisheries Monitoring Centres (FMCs). In addition, VMS can be used for search, rescue, and maritime safety purposes.

The data registered by these systems allows specialists to use them in the prevention of IUU fishing. Readers interested in a detailed comparison of the advantages and disadvantages of AIS and VMS are referred to [43].

Coastal Surveillance System (CSS) consists of video systems using CCTV and long range cameras in ports and harbours, and maritime radar systems such as Costal Surveillance Radar (CSR). These tools support the security services by detecting vessels within their range in a real time. These systems provide basic information on the movements of vessels in territorial waters and exclusive economic zones.

C. ALGORITHMS FOR DATA ANALYSIS

The sensors placed on autonomous units from Section II-A and the systems described in Section II-B provide vast amounts of different data, ranging from location time series to images. The aim is to find a way to process this data in order to, for example, find patterns or detect anomalies. Many different types of algorithms are used for this purpose, but since this problem is a Big Data problem, ML especially Deep Learning (DL) algorithms are the ones that perform most effectively. ML is a field of artificial intelligence focused on algorithms that improve themselves automatically through data exposure. It draws from general computer science methods such as data mining, statistics, pattern recognition, neural networks, and cognitive science. Most commonly, the subsequent steps of ML system operation include: data preprocessing, data fusion, feature extraction, model selection, model training, and prediction.

There are many methods of data preprocessing, and listing them is beyond the scope of this article. Nevertheless, it is one of the most important steps which determines the quality and effectiveness of further algorithms. The most important elements considered in preprocessing are: data cleaning, data transformation, and data reduction.

As mentioned, the IUU fishing is detected based on analysing data of different types (signals, images, tabular data) received from many different sources (e.g. CCTV, AIS, VMS, CSR). In this case, it is often necessary to use data fusion methods. There are number of definitions of data fusion, one of the most accepted by scientists is that provided by the Joint Directors of Laboratories (JDL), which says that data fusion is a multi-level process dealing with the association, correlation, combination of data and information from single and multiple sources to achieve refined position, identify estimates and complete and timely assessments of situations, threats and their significance [45].

After proper processing and skillful combination of data from different sources, the data can be analysed to find the searched relationships. The most common tasks are: clustering, classification, detection, and segmentation.

Data clustering is the task of grouping a set of samples in such a way that those in the same group (called a cluster) are more similar (in some sense) to each other than to samples in other groups (clusters). Examples of clustering methods are k-means [43], hierarchical [44] or DBSCAN [45].

Classification is the process by which input samples are assigned a specific category (class). There are many methods of classification. The basic ones are K-NN [46] and SVM [47], as well as those based on neural networks, either classical [48] or deep neural networks [49], [50], [51].

Object detection is defined as localization of an Axis-Aligned Bounding Box (AABB) and classification - assignment of a label. Nowadays, the most state-of-the-art algorithms used in this field are those based on deep neural networks [52] due the fact that they significantly outperform the classical ones. The most common architectures among them are SSD [53], YOLO [54], [55], [56], R-CNN [57], and its successors such as Fast R-CNN [58] or Faster R-CNN [59].

Segmentation is the process of assigning a label to every pixel in an image in such a way that the pixels with the same label share certain characteristics. Again, the field has been dominated by algorithms based on deep learning. Here, Mask R-CNN [60], being an extension of Faster R-CNN, or U-NET architecture [61], were introduced. Optical Character Recognition (OCR) is an example of the use of segmentation.

The differences between these tasks are depicted in Figure 7, using the analysis of the image showing a fishing gear as an example.

These algorithms can find patterns in the data (clustering and classification), detect anomalies (clustering and classification), perform image processing (all 4 algorithms), track objects (detection and segmentation), group objects (clustering), and more. Due to the variety of ML approaches, tools, and algorithms that can be used in this topic, a thorough characterization of them is beyond the scope of this review. The readers interested in the details of machine learning solutions are referred to review papers from dedicated areas [62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73].

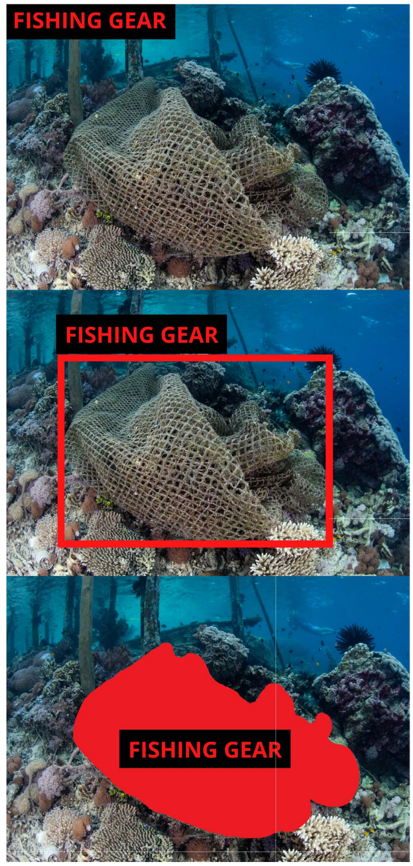

FIGURE 7. Classification, detection and segmentation of fishing gear.

III. OVERVIEW OF MOST RELEVANT APPROACHES AGAINST IUU FISHING AND ITS IMPLICATIONS

Effective prevention of IUU requires the surveillance and tracking of fishing boats. This can be achieved mainly by analysing historical data related to vessel trajectory and timing of operations, and by monitoring entry and exit from harbours and ports. The systems that monitor fishing activities can catch incorrect behaviour, anomalies, and/or inconsistencies in the data recorded by tracking systems, which will imply suspicious activity or intentional deception of the system. The overview was divided into three sections: (III-A) boat tracking approaches related to the analysis and verification of data containing the information on vessel trips and fishing activities; (III-B) ghost fishing approaches related to the removal of nets and their prevention through damage detection; and (III-C) autonomous systems on which the algorithms presented in the following subsections may be implemented.

A. BOAT TRACKING

One of the ways to detect illegal fishing is to utilize AIS data and compare it with radar or satellite data. All legally moving vessels conducting fishing should be visible in the AIS. Recognising whether the fishing is carried out according to regulated, authorised methods is a more difficult task. In this section, the reader is introduced to the issues of port monitoring and AIS/VMS data in cooperation with advanced intelligent systems. The surface vehicle surveillance equipment is shown in 8. The satellite and radar data (1, 2, and 3) provide historical and real-time positions of vessels fishing and moving in the area specified; satellite imagery (4) provides images to verify the position of the fishing vessels; the vision systems (5) provide information on vessel plate numbers, as well as the start and end times of trips. Illegal activity can be detected through appropriate data fusion, preprocessing, tracking data analysis, pattern recognition, etc. Many ideas and approaches to these problems can be found in the literature [21], [22], [23], [24], [25].

The papers described in this section refer to different types of fishing gear. Figure 9 presents conceptually selected examples of different types of fishing gear, while the rest of the article discusses different approaches of the researchers to this topic.

An interesting approach to analysing IAS data to identify the type of fishing by surface vessels is provided in [21]. The aim of the authors was to recognize four types of fishing gear (Purse seine, Trawl, Longline and Fixed gear). To achieve this, they proposed a system based on the Supervised Autoencoder Dimensional Reduction (SA-DR) algorithm and the IAS data set called the ”Anonymized AIS training data” obtained from the Global Fishing Watch platform. The paper

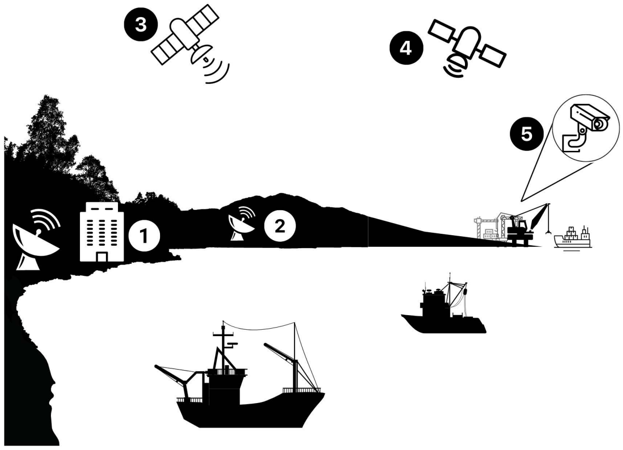

FIGURE 8. Examples of boat tracking systems. 1. Fisheries monitoring centres; 2. Coastal radars; 3. AIS/VMS satellites; 4. SAR satellites; 5. CCTV harbour monitoring.

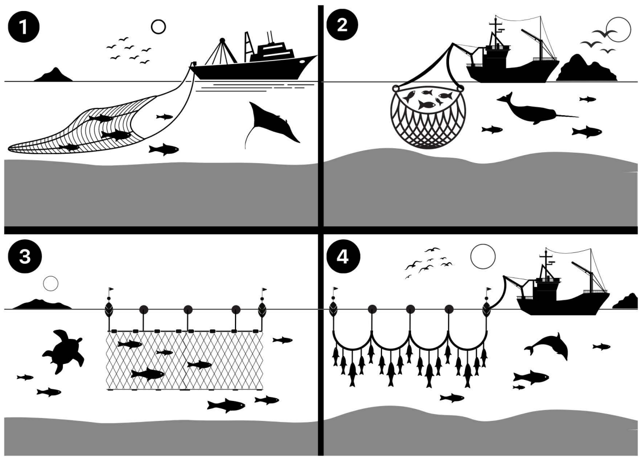

FIGURE 9. Fishing gear types. 1. Bottom trawl; 2. Purse seine; 3. Gillnet; 4. Longline.

describes the application of known DR methods called IVIS and CE to obtain data in two-dimensional space. The authors then present the results of fishing gear recognition using four classification methods: K-Nearest Neighbors (K-NNs), Naive Bayes (NB), Linear Support Vector Machine (L-SVM), and Radial Basis Function SVM (RBF-SVM). By using classification for reduced dimensional data, an accuracy of about 95% was obtained for all classification methods used. In addition, the authors make all the data and code used in the paper publicly available. In the future, the proposed approach is expected to use such data on trajectory, position, and travel times of fishing boats recorded using AIS and VMS, and then to recognize the fishing gear, thus facilitating the identification of the fishing method. The authors point out the need for future research into automating the preprocessing data stage of the presented solution, so that it can be used for real-time analysis of AIS or VMS data.

Another approach to the analysis of fishing vessels' routes was presented in [22]. The authors analysed the fishing

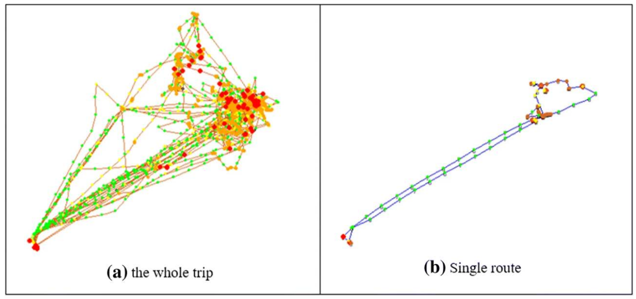

FIGURE 10. Recognition of a single route [22].

vessels' routes presented as GPS data obtained through VMS and AIS systems. In their solution, they utilized the Knowledge Discovery in Databases (KDD) method to extract single routes and points of interest (i.e. points where fishing was potentially carried out). The analysis took into account the trajectory, time, and speed of vehicles. Four types of fishing activities were recognised (Purse seine, Trawl, Longline and Reefer). The authors managed to collect data of 771 fishing trips for Thai fishing vessels using four types of fishing gear. The recognition of a single route (Figure 10) was achieved through the DBSCAN algorithm [45]. Then, using K-NN with Dynamic Time Warping (DTW), route fragments were obtained and labelled as fishing, non-fishing, and transshipment activities. Next, the data was used as additional input nodes which, together with the statistical characteristics of the individual route, were processed by a Multilayer Perceptron (MLP). By using an additional processing layer that recognised activity areas, the authors were able to achieve over 97% efficiency for Trawl, Longline, and Reefer, and 90% for Purse seine.

Another solution for tracking fishing vessels is presented in [74]. The authors focus on identifying fishing activity using the Gaussian Mixture Model (GMM) combined with Random Forest (RF) and SVM methods. The analyses presented are based on vehicle speeds and courses provided by the VMS. The authors propose a two-stage approach, which in the first phase uses unsupervised learning (GMM) to identify common features of groups of data. Then the classification of one of the four types of fishing gear (Purse seine, Trawl, Longline, Pole and line) is applied with the advantage of supervised learning using RF and SVM. The method proposed by the authors of [74] allowed to obtain about 95% efficiency for Trawl, Pole and line, and Purse-seine recognition, and about 89% for Longline. Further research and comparison of the solution proposed in 2015 with the Gaussian-Von Mises Mixture Model (GvMMM) method are presented in [75].

Analysing vessel trajectories through GPS data is not the only way to track fishing activity. The authors of [23] presented the use of video systems including CCTV cameras located in ports to recognise and record numbers and names identifying vessels. In addition to presenting a solution for detecting and recognising the plates, the authors draw attention to the problem resulting from missing standards on plate number labels (skewness, different font size and use of non-contrasting colours). The solution described by the authors consists of three steps: vessel detection, highlighting the Region of Interest (ROI), and OCR plate recognition and extraction. The authors use well-known tools available in OpenCV and MATLAB.

The analysis of motion trajectories and the behaviour of fishing vessels from North American coastal waters is presented in [24]. The authors use AIS data from five years, 2010 to 2014. In total, 250,000 trips of almost 800 vessels were extracted. The data analysis was performed by clustering using the DBSCAN method. The aim of the research work was to detect anomalies in the pattern of ship motion, represented as a trajectory with specific start and end points, such as ports and/or known anchorages. In their work, the authors also introduced a ranking system, allowing for long-term analysis of suspicious behaviour of selected vessels. This made it possible to track the frequency of potentially illegal activities, not just detect them. The authors point out that fishing activity is usually carried out as a trip, so appropriate data clustering should identify strong patterns within similar trips. The analysis distinguishes between two types of anomalies: global and local, so that the detection of suspicious behaviour takes into account the deviation from the pattern as well as anomalies within a given trip. The authors indicate that the aim of their further work on the algorithm and data analysis is to use VMS data.

A different way of suspicious vessel activity detection is presented in [25], where the authors use data from AIS and satellite (Sentinel-1A and ICEYE-X2), in particular from English Channel and Solent. The key feature of the presented solution is the use of correlation and matching of the data available in AIS with that recorded by the spaceborne Synthetic Aperture Radar (SAR). In addition, it allows detection of ships carrying out trips with completely or periodically turned off AIS, which increases the traceability compared to previously described works that relied mostly on anomaly detection of AIS data. The pipeline of the system is very complex. To gather adequate quantity and quality of data, the authors used the idea of data fusion. Then, they applied transfer learning to initialize the model parameters. Finally, the vessels captured in the SAR images were identified. The results of classification were compared with the AIS traffic records to check the consistency of positions between data from two independent sources.

Additionally, the Random Undersampling Boosting (RUSBoost) [76] algorithm was employed to classify the six vessel types. The model was first trained on AIS data and then transferred to make predictions on SAR ship detections. The authors mention the use of such methods as Global Nearest Neighbour (GNN) and the Jonker-Volgenant algorithm [77]. Presented results show a high level of compliance and therefore confirm the usefulness of the model in detecting surface vessels performing suspicious activities.

Another solution for fishing activity surveillance is the detection and location of vessels carrying out fishing, with

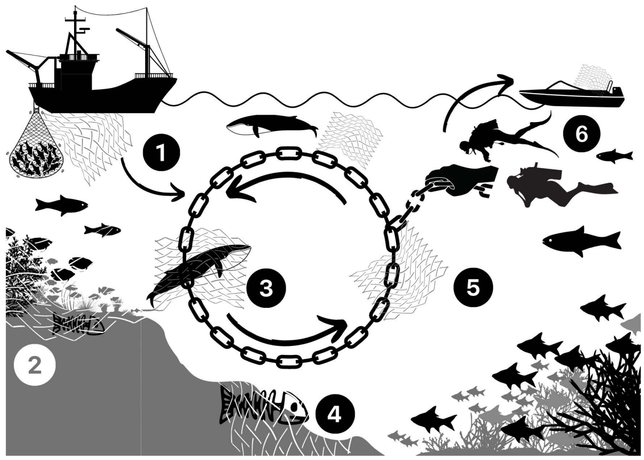

FIGURE 11. Ghost fishing cycle. 1. Loss or abandonment of fishing gear; 2. Reef degradation and fish kills; 3. Wildlife killed by nets drifting into open water; 4. Nets sinking to the seabed weighted down with dead wildlife; 5. Nets rising to the surface due to weight loss; 6. Breaking the cycle by human intervention.

subsequent classification of the hull plate, presented in [26]. The solution uses computer vision systems placed on a remote-controlled UAV patrolling the area. The tasks of detection and localization is performed using deep convolutional neural networks. This method assumes the use of a database containing hull plates of legal surface vessels. The text recognition is realised by means of OCR, similarly as in [23]. The text recognised on the side of the analysed vessel is compared with the database, looking for a match. The lack of hull plate in the database suggests illegal fishing. Image feature extraction is performed using the Scale-Invariant Feature Transform (SIFT), and matching is performed using K-NN. The system presented by the authors is designed for real-time operation, as opposed to the aforementioned solutions.

B. GHOST FISHING

The increased level of IUU fishing correlates with the higher level of ghost fishing within the area. Figure 11 shows a deadly ghost fishing cycle that can be broken only by human intervention. Ghost fishing has detrimental impacts on fish stocks and potential unfavourable effects on endangered species and benthic environments. ALDFG may entangle and lead to the deaths of larger marine animals and sea birds, transport invasive alien species, and disturb spawning grounds and smother habitats, thereby serving as major hazards and a long-term threat in marine environments. Furthermore, synthetic nets are transformed into microplastics as a result of degradation. ALDFG also results in both economic and social costs that can be significant. For this reason, ALDFG, which is a growing global problem, is drawing significant attention [12], [78].

Various ways have been invented to deal with the ghost fishing problem and break the mentioned cycle. These include using biodegradable nets, ensuring that the equipment contains features such as lights, beacons, or owner tags that reduce the chance of being lost, designing gear to minimise fishing effectiveness after a short period of no maintenance, and creating a map of lost gear [79], [80], [81].

Another effective way to deal with ghost fishing is using artificial intelligence-based solutions in order to prevent gear loss by early defect detection [27], or to recognize ALDFGs by UAVs [82], underwater cameras and UUVs [28], [29], [30], sonars [31], [32] or laser scanning systems [33].

In [27], an automatic gillnet monitoring system was developed using an ANN-based machine learning system with data generated from simulations under different environmental conditions. The purpose of that study was to detect the initial failure of the gillnet so that the fishermen could collect it before progressive failure occurs. To learn and validate the system, the authors employed the training data consisting of nine sea states with three significant wave heights and three peak periods, as well as the test data consisting of two sea states, different from those used in the training data. The experiments included 23 gillnet states, i.e., the intact state and 22 damaged states. In order to detect net damage, the authors proposed a model based on artificial neural network. The ANN consisting of 2 hidden layers was trained in a supervised manner. To update weights and biases, the scaled conjugate gradient method was used. A total of 17 inputs were selected, namely, wave heights, peak periods, x-y-z accelerations at four locations, and x-y-z displacements of the location-buoy centre. There were 23 outputs nodes, one for each gillnet state. Output 1 marked a damaged net, whereas output 0 indicated an intact net. The node number with the largest prediction value among these 23 nodes became the predicted damage indicator. The number of hidden neurons that gave the best results was 180 in each layer. The best prediction accuracy was 99.5% and 91.1% for training and test cases, respectively. Additionally, after attaching a median filter, the prediction accuracy increased to 99.7% and 96.0%. The results presented in [27] have shown that such a system may be successfully applied. By early detecting fishing gear damage, it is possible to counteract net loss and the resulting ALDFG.

In [82], the authors focus on drone-based prevention of crab trapping in an estuary in New South Wales (Australia). The experiment utilized a quadcopter drone with inbuilt camera sensor. A series of flights were performed to gather the training data. During each flight, the pilot manually searched for and identified traps. The human effort and the amount of financial cost necessary to process the video-derived ghost net data are significant. Therefore, there is a need for developing automated and more cost-effective methods to reduce them. IUU often targets crab species found in estuarine habitats due to a financially profitable sale, the species being an easily accessible resource, and because of little investment in fishing gear needed in harvest. To the best of the authors' of this paper knowledge, there are no solutions in use that automate detection of crab traps or ghost nets by drones. The automation of the drone-based process to counter ghost fishing should be pursued. There are many studies (e.g. [83], [84], [85], [86], [87]) confirming the effectiveness of small object detection using UAV-based imagery and Deep Learning (DL).

In [28], the authors designed an underwater agent vehicle system that combines small agent AUVs and a large main AUV. The ghost net recovery algorithm that can automatically detect, grip, and lift ghost nets was implemented. In order to detect ghost nets, the DNN called tiny-YOLOv3 [55] was applied. The network was trained with 800 net images. After the training, the vehicle was able to detect ghost nets in real time. Unfortunately, more details related to the model were not provided by the authors.

Another system that uses underwater images to detect ghost nets was proposed in [29]. The authors focused on a sea debris detection. Their model identifies three types of marine litter: artificial, natural, and plastic which consists of e.g. plastic bottles, plastic bags, bamboo and fishing nets. The system is based on DNN called Inception [88]. As a backbone net, the system utilizes ResNetV2 with weights pre-trained on the ImageNet dataset. The fully connected layer head was removed and replaced with a new multi-output prediction layer head. The output of the network was flattened and given as an input to two new branches, the first of which was responsible for bounding-box prediction, while the second one predicted the class label of the observed object. In these branches, the mean square error and the categorical cross-entropy were used as the objective functions, respectively. The system described in [29] predicted the class label with 96% accuracy and the bounding box with 82% accuracy.

In [30], another system focused on detecting marine debris including ghost nets was described. The authors present an object detection approach based on DNN with the aim to automatically detect seafloor marine litter in real-world environment. The DNN was based on Mask R-CNN [60]. MobileNetV1 [89] with weights pretrained on COCO dataset (a commonly used benchmark dataset used in DL) was used as a backbone. Seafloor imagery was acquired through a towed underwater camera. The training and testing data included 635 video frame images of 1920×1080 pixels. Eleven categories of trash were distinguished, including fishing nets. In total, 1166 litter items were manually identified and labeled with bounding boxes. The dataset was augmented with horizontal and vertical flip, brightness change, and noise addition. Additionally, the images were resized to 832×448 pixels. After data augmentation, the size of the new dataset increased to 3910 images. Trained by [30], the network achieved mAP_{50} of 62% over all litter classes. In several litter types (plastic bags, fishing nets, tires, plastic caps), the network was even more effective, reaching an average precision of over 79%.

In [31], a new method to detect underwater regions of interest in real-time using side scan sonar imagery was described. The proposed system was trained in an unsupervised manner, which made it applicable to domains such as underwater archaeology or ocean waste management, where direct recognition is not always possible or reasonable, either because

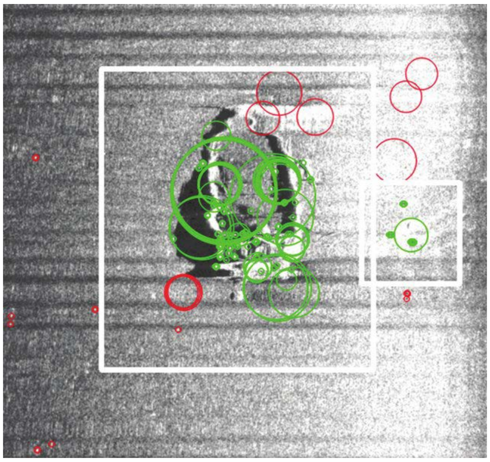

FIGURE 12. Unsupervised extraction of underwater ROI [31].

of the difficulty in collecting enough data or because of the overwhelming diversity of possible targets. The method consists of three stages. The first stage is image synthesis from sonar data, which results in a geometrically and radiometrically corrected output image suitable for automated analysis. In this stage, slant-range correction and histogram equalization were applied. The second stage involves feature point generation. It is inconsistent with the fact that objects in images can be expressed as a large set of smaller visual features. The algorithm rests on the premise that the density of visual features increases inside regions of interest. Two feature detectors: Features from Accelerated Segment Test (FAST) [90] and Maximally Stable External Regions (MSER) [91], [92], were used to generate feature cloud. The third stage is based on clustering the point cloud by the DBSCAN algorithm, which simultaneously provides denoising. As soon as the point cloud is clustered, the centroid can be used to define a bounding box for ROI. The feature cloud generated by FAST and MSER algorithms can be observed in Figure 12, where the features are marked with circles. After that, the clustering algorithm DBSCAN groups them or rejects as noise (green and red colours, respectively). Next, the bounding boxes (white) for each ROI are generated. The dataset consisting of lost/abandoned fishing gear ($n = 6$) was manually investigated by a human operator who identified ROIs and their centres. Automatic gear detection resulted in the accuracy of 72.7%.

In [32], the authors presented an interesting approach using sonar-derived imagery. The main goal of the proposed system was to identify underwater fishing nets and thus to avoid irreparable damage caused by them to AUVs. In the opinion of the authors of this paper, the described approach has shown that sonar-based imaginary also has a great potential to prevent ghost fishing. Since the proposed application was to run in real time, a trade-off between accuracy and speed had to be achieved. For this reason, the Multiple Receptive Field network (MRF-Net) was used. It is a network inspired by the CenterNet [93], that bases on an anchor-free approach. The input images are fed into the Fully Convolutional Neural Network (FCN) [94] that generates a centre-point heatmap which is then used to predict object centres. The structure of the MRF-Net net can be divided into two parts: the feature extraction network, which is mainly responsible for fusing different levels of features from Forward Looking Sonar (FLS) images, and the prediction module, which is responsible for locating the boundary box of the object. A novel backbone network was proposed, that has depth-wise convolution with reduced number of parameters and a multi-branch block using dilated convolution to provide the multi-scale of receptive fields. Furthermore, a combination layer of the instance and batch normalisations was used to improve the generalization performance of the proposed network with no additional computation. The dataset consisting of 18332 images was collected with a multi-beam forward-looking sonar. More technical parameters of the sonar are available in [32]. In order to obtain an image from the forward-looking sonar, the interpolation algorithm based on bilinear interpolation was used. The dataset included three kinds of obstacles at different distances (0–5 and 5–10 m): fishing net, cloth, and plastic bag. The proportion of each category in the dataset was equal.

In this approach, automatic detection reached 90.3% of mAP_{50} for all categories. For fishnets, it was 91.8%. For real-time applications, the speed of performance is also important. This approach achieved a rate of 11.13 frames per second.

A similar approach to avoiding ghost nets to prevent damage to AUVs, which can be directly applied to ghost fishing prevention, was presented in [33]. This approach used imaging based on laser scanning. Furthermore, the authors recognized the problem of insufficient amount of data for training a DL model and therefore used Generative Adversarial Networks (GANs) to generate the artificial data. The proposed system consisted of data collection, data amplification, and target detection. The laser scanning system is insensitive to temperature and salinity of water. Moreover, it provides high brightness and effectively eliminates background noise. All this enabled fast detection, along with high precision and a large detection area. Because of light-transparent window of the sea, green laser light was chosen. The laser was used together with an underwater camera to obtain dynamic videos of fishing nets for subsequent detections. The deep convolutional generative adversarial network was used to generate artificial data.

C. AUTONOMOUS SYSTEMS

Autonomous vehicles are directly related to detection, identification, and classification of IUU fishing without human intervention. The algorithms discussed in other sections are implemented on board of autonomous units (Figure 13). This subsection does not present the problem of autonomous vehicles in detail, but simply points out solutions that are already in use in the fight against IUU.

Autonomous patrols capable of identifying threats are a significant support to coastal inspection services. Fishing

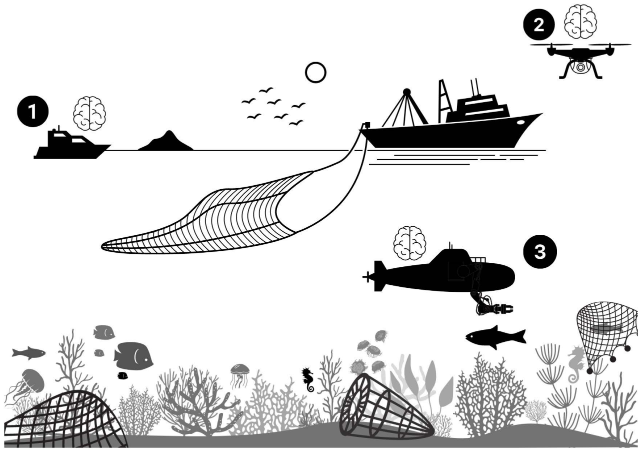

FIGURE 13. Autonomous systems. 1. USV; 2. UAV; 3. UUV.

zones or restricted sea zones are vast areas that would require significant human and equipment resources to be patrolled continuously. The introduction of autonomous patrolling units in the form of UAVs and USVs equipped with AI-based detection and recognition algorithms could increase the effectiveness of IUU fishing detection. According to [38], the operational costs of USVs and UAVs are approximately 0.025 $US per square kilometre of patrolled space, which is an order of magnitude lower than for traditional manned units, which cost 0.27 $ US per square kilometre. The use of satellite imagery to track and analyse the trajectory of fishing vessels is also significantly cheaper at around 0.036 $ US per square kilometre of coverage. Interesting applications of USVs in the fight against IUU fishing are presented in [38], [39], [95], and [96].

In [97], the authors present the Buscamos solar-powered autonomous surface vessel that allows patrolling large marine areas. The ASV has been equipped with multiple sensors to collect data about the environment, i.e. sonar (underwater and side scan), laser and vision systems, and depth or wind sensors. Adequate ASV equipment is necessary for proper collision-free navigation, and the number of sensors used allows the data to be used in other systems, such as those detecting suspicious vessels. The presented unit performs the function of both atomic vehicle and oceanographic observatory. The authors of that paper present a system using fuzzy logic to make decisions ensuring energy and navigation autonomy. The paper describes both the technical details and the software architecture of the presented approach, focusing on providing an efficient energy system, for long-term autonomous missions. The performance of the system was verified during a 10-day mission in which the ASV covered a distance of 92.28 km. Additional work related to the use of the Buscamos USV in connection with countering IUU fishing is presented in [39], where the authors describe the use of AI Recognition to detect and classify marine vehicles conducting suspicious activities.

Another project presenting a solar-powered surface vessel is described in [97]. The authors have developed a concept for an autonomous vehicle designed to work with UAVs. The presented surface vessel is supposed to allow the UAV to take off, land, and recharge, thus increasing the range and operational capabilities of the drone. In their work, the authors focus on hardware and software design and technological aspects of the heterogeneous system. Among other things, the paper describes the mandatory hardware for autonomous behaviour, the hardware architecture of the system, and the UAV docking platform. The presented solution could be an effective tool in the fight against IUU.

TABLE 1. Categorization of papers by equipment, systems and algorithms for boat tracking and ghost fishing detection.

		boat tracking	ghost fishing
Equipment	Aerial	[26]	[82]
	Surface	[38, 39, 95, 96]	-
	Underwater	-	[28–33]
Systems	AIS/VMS	[21, 22, 24, 25, 74, 75]	-
	Vision systems	[23, 25, 26]	[28–30, 82]
	Radar, sonar, laser	-	[31–33]
Algorithms	Classification	[21, 22, 25, 74, 75]	[27]
	Clustering	[22, 24]	[31]
	Detection	[26]	[28–33]
	Segmentation	[23, 26]	-

IV. DISCUSSION

In order to facilitate the review of the papers discussed, they are summarized in Table 1. It categorizes the described papers by equipment, systems, and algorithms. In addition, we proposed three scenarios in Section IV-A using the described equipment indicating their strengths and weaknesses.

IUU fishing is not only a problem for local communities but a global problem affecting various parts of the world (e.g. Thailand [22], Indonesia [26], [75], North America [24], United Kingdom [25], Portugal [23]). Not only does it affect the economy but also the environment. Although this phenomenon was defined over 20 years ago, the fight against it is still not finished.

In recent years, modern algorithms have been increasingly used to effectively counter IUU fishing and its consequences. To the best of the authors' knowledge, this paper is the first to provide comprehensive knowledge of the approaches used to tackle this phenomenon. In the paper, we focused on engineering solutions, instead of regulatory ones. However, the authors would like to point out that this paper is not a systematic review of the various techniques presented. Authors' intention was to familiarise the readers with the most up-to-date and promising solutions and to indicate a good starting point to initiate research into a holistic system, which would be an fusion and extension of the indicated solutions. The analysed approaches were divided into those related to boat tracking and those related to ghost fishing detection. The former is the best explored issue of counteracting IUU fishing. Usually, it is based on historical records of fishing boat trajectories obtained from AIS/VMS, and on that basis detects potentially illegal behaviour. The analysis of these trajectories typically consists of classification based on the location of vessel, and characteristic behaviour of the vessel with relation to the fishing gear used. Being aware of where the fishing is taking place may provide a conclusion about the its legality. Furthermore, additional identification of the type of fishing gear used may indicate whether the fishing has been properly reported, and whether it was carried out in accordance with the regulations of the area at the time. The results from the works [22], [74], [75] indicate that there is difficulty in separating longline and purse seine. Based on the presented data, it can be estimated that about 5% of the catches identified as longline are in fact made using the purse-seine method. However, the analysis of vessels trajectories based on AIS/VMS data also has its drawbacks. The primary one is that these systems use mostly historical data. For instance, the detection of an individual who carried out illegal fishing several years ago only gives the information about such an event, but it does not allow to draw legal consequences against the individual. There is a lack of systems analysing data in real time, which would make it possible to catch an individual in the act. The secondary drawback is that there is the possibility of periodic disabling or complete absence of the AIS/VMS system on a vessel, and therefore the lack of data to analyse its behaviour. This problem can be solved by using complementary approaches. One of them is the verification of data coming from AIS/VMS with image data coming from SAR satellites or CCTV systems. However, for ship identification systems based on cameras in ports and harbours, the biggest problem is the lack of uniform standards concerning ship plate numbers, which would facilitate the use of intelligent vision systems for real-time ship identification.

The papers [31], [32], [33] described technologies commonly known for autonomous vehicle solutions, so-called ranging systems. Ranging systems include radar, sonar and lidar; however, long-range radars, due to their energy consumption and size, are not components of small unmanned vehicles and therefore are rarely used in detecting ghost nets. They are, however, used as part of CSS. Ranging systems are well researched and widely used tools, so the authors of the paper decided not to focus on their technological aspects, but only point out the features of these devices in the context of countering IUU fishing, as well as its consequences (ghost fishing). Radars have the advantage of range as well as low susceptibility to poor weather conditions such as fog. However, they can be interfered with by other signals and are unable to identify the type of object. Radars in the context of IUU are used to detect vessels in water areas. Lidars are a common technology in robotics, and are the basic sensors for autonomous vehicles enabling accurate navigation. When they are used on water surfaces or where the surface is not uniform, they may not return accurate data since high water depth will affect the reflection of the pulses. This makes lidar not a desirable technology in surface vessels, however, the authors of [33] point to the potential of using laser technology in detecting ghost nets. Sonars, on the other hand, are a technology dedicated to maritime solutions. They allow the detection of undersea objects such as ghost nets, but the increasing number of sonars in use is contributing to an increase in noise pollution in the oceans, which confuses marine animals that use acoustic waves to navigate and communicate with each other. Some sonars are even capable of permanently damaging animals' hearing.

The fight against IUU fishing is crucial, as it results in the ability to effectively manage fisheries, reduce overfishing, reduce destructive exploitation, restore the balance of ecosystems, support the conservation of endangered species, and reduce the informal economy. However, preventing IUU fishing unfortunately results in increased rate of ghost fishing, as fishermen abandon their gear in fear of punishment. Therefore, fighting IUU fishing alone is insufficient given the fact that ghost fishing must be countered as well. It is usually performed by ghost net detection, which allows picking the nets out thus breaking the ghost fishing cycle. Such detection systems are usually based on both vision and ranging (radar, sonar, lidar) systems. To automate this process, these systems should be placed on autonomous platforms. Drones allow inspection of shallow waters, whereas UUVs aid detection of fishing gear in deeper areas. When compared with the detection by UUV and UAV on-board systems, the systems placed on USVs are ineffective. USVs cannot conduct detection of fishing gear in deep waters, whereas in shallow waters, drones have a much higher mobility and a broader visual field. Current systems are used to avoid collisions between UUVs and fishing gear; however, they can be applied directly to detect ghost nets, return the information about their location, and assist in pulling them out. To the best of the authors' of this paper knowledge, there are no systems that employ AAVs in ghost net detection. The real-time detection of ghost nets allowing for emergency response is the area in need of extensive development.

In addition to the directions of further development mentioned above, the authors believe that the most significant is development of practically effective holistic systems that clearly indicate IUU fishing. Currently, each system elements, such as algorithms using CCTV or AIS/VMS data, can only be evaluated individually and used independently, hence their potential is not fully exploited. They often perform the same tasks (e.g., fishing gear type detection) but use different data, or they perform tasks that do not directly relate to counteracting IUU fishing directly but only have a predisposition for such use (e.g., ghost net avoidance). In order to develop a holistic system in greater depth, it is necessary to explore the individual issues on their own. However, this paper provides a good starting point for further exploration of the topic and provides references to many valuable sources.

Some of the reviewed papers reported precise values showing the efficiency of the algorithms used. These include, for example, accuracy or mean averaged precision. However, these results were obtained on very different datasets, as well as by operating for a different purpose (e.g. ship detection, detection of various types of fishing equipment), therefore it is not methodologically correct to compare performance between these algorithms.

In summary, modern methods do support the countering of IUU fishing and its consequences. USVs and the AIS/VMS data are typically used to track boats. The most common task performed in this field is classification. Preventing ghost fishing typically uses UUVs equipped with vision or ranging systems to perform detection tasks. In the future, a holistic system consisting of the components described in this paper is expected to be developed to effectively counter IUU in real-time. Another proposed future research direction is to conduct a review of current solutions in the context of global and local policies regarding countering IUU fishing in order to find weaknesses and opportunities for improvement.

A. APPLICATION SCENARIOS

Scenario I: Detecting suspicious boat behavior suggesting illegal fishing in coastal waters, detecting ghost nets in shallow waters.

Equipment: Aerial Vehicle with camera, Surface Vehicle with camera, plate recognition by CCTV.

Discussion: Aerial and surface vehicles are suitable for patrolling shallow waters. They should patrol mentioned area, if suspicious behavior or ghost nets are spotted, they should verify it and call for relevant law enforcement authorities if confirmed. However, aerial vehicles have a short operating range due to their battery capacity and are vulnerable to bird attacks. Surface vehicles can be equipped with their own power source, such as solar panels and can therefore patrol the waterfront continuously. Both types of vehicles are sensitive to weather conditions. Despite these drawbacks, these vehicles are, as shown according to the mentioned earlier literature, used for patrolling coastal waters and can be used successfully in this scenario. In addition, we suggest that vehicles should be supported by coastal monitoring, which would help detect suspicious boats as described in the section III-A about hull plate recognition. However, it should be emphasized that at the moment, unfortunately there is no standard for the appearance of hull plates and therefore recognizing them is a challenging task.

Scenario II: Detecting IUU fishing in offshore areas.

Equipment: Surface Vehicle with camera, AIS/VMS

Discussion: We suggest using satellite tools to detect suspicious behavior of boats, and then sending a surface vehicle to confirm, which will conduct observation and then call for relevant law enforcement authorities if necessary. Currently, AIS/VMS use historical data, but as a result of further development of dedicated algorithms and a sufficiently comprehensive database, it will be possible to use them in real time. Section III-A described in more detail the use of AIS/VMS in the context of detecting suspicious boat behavior. The disadvantage of using a surface vehicle is its limited field of view through waves and sea conditions, as well as the inefficiency of this technology in the context of detecting ghost nets.

Scenario III: Detection of ghost nets in an area with an increased risk of their occurrence

Equipment: Underwater Vehicle with sonar, AIS/VMS

Discussion: We suggest using satellite tools to identify an area with an increased risk of ghost nets, as a result of increased levels of IUU fishing there. An underwater vehicle should then be deployed to the area to locate and catch ghost nets. The ghost nets could then be handed over to manned patrols. The disadvantage of such a solution is that a manned patrol has to transport the underwater vehicle to a given location, but after that the search of the area is carried out autonomously. Detection of ghost nets was discussed in more detail in Section III-B. The advantages of using sonar are its relatively low cost, independence from surface conditions, and that it works well in underwater environments. However, it should be remembered that it creates a noise pollution in the water and is not indifferent to wildlife.

V. CONCLUSION

This paper provides fundamental information and definitions related to illegal, unreported, and unregistered fishing and its consequences in the form of ghost fishing. The genesis of the problem is outlined, as well as its short and long-term effects. Attention is paid to the legislative aspect of the problem. The main objective of the paper was to present recent approaches of combating this phenomenon using modern, innovative methods. It presents achievements in this field over the last few years.

The equipment and systems that provide the data, as well as the algorithms that process it, have been presented. Furthermore, current application developments were highlighted. Two main problems were identified, the first one related to tracking boats to detect anomalous behaviour that may suggest illegal activity, and the second one related to countering the consequences of IUU fishing in terms of increased levels of fishing occurring outside of human control. Additionally, the potential for the use of autonomous units and the lack of current systems were pointed out. It should be stressed that the problems identified in the paper and their causes are very complex, so their effective solution will only be possible with a comprehensive approach taking into account legal and technological background.

The authors believe that the paper has highlighted the relevance, complexity, and magnitude of the problem that is IUU fishing, thus creating a starting point for further research.

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