INTERNATIONAL JOURNAL OF
COASTAL, OFFSHORE & ENVIRONMENTAL ENGINEERING

Available online at: www. Ijcoe.org

A Critical Review of Challenges and opportunities in Using Remote Sensing and Image Processing for Rip Current Studies

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ARTICLE INFO

Article History:
Received: 14 April 2025
Accepted: 03 May 2025

Keywords:
Rip currents
Surf zone
Remote sensing
Machine learning
Artificial intelligence

ABSTRACT

Rip currents, often appearing as mushroom-shaped features within the surf zone, are a primary cause of swimmer drownings along beaches worldwide. Due to their transient nature, the application of advanced remote sensing and computer vision techniques for localized detection of these phenomena significantly mitigates the limitations traditionally associated with their study. In addition to these methods, the emergence of machine learning and artificial intelligence (AI) techniques provides powerful tools for a more precise investigation of rip currents, offering substantial support to remote sensing approaches and enhancing the efficiency of coastal lifeguard operations on larger scales. This study aims to present a comprehensive review of the relevant literature from 2014 to 2023, evaluating both traditional and modern approaches to analyzing the behavior of these coastal currents. Particular emphasis is placed on examining the conducted studies, including details on the categorization of research objectives, comparison of various tools, and exploration of associated opportunities and challenges.

1. Introduction

Rip currents are narrow, jet-like flows that move seaward from the vicinity of the shoreline, typically forming in the presence of irregular seabed topography, especially when incoming waves approach the coast nearly perpendicularly [1]. These currents constitute a significant component of the nearshore circulation system and can induce local bathymetric changes by carving flow channels [2]. Moreover, they play a vital role in coastal sedimentary and hydrodynamic processes, contributing to sediment transport and the dispersion of organisms and pollutants along the shoreline, thereby acting as influential agents in coastal dynamics [3].

On the other hand, due to their often rapid and transient nature, rip currents have become one of the most serious coastal hazards for swimmers in many parts of the world [4]. Consequently, understanding the dynamic behavior of rip currents is crucial for enhancing beach safety and, more broadly, for effective coastal zone management [5]. These currents are influenced by various factors such as wave height, wave direction, and shoreline morphology and are categorized into several types, including shear instability rips, flash rips, channel rips, focused rips, deflection rips, and shadow rips [6]. However, since the formation of rip currents is governed by complex hydrodynamic processes and the natural variability of the coastline, monitoring them is highly challenging—particularly given the wide range of rip types that may develop under diverse coastal hydrodynamic and morphological conditions during field observations. In addition, in-situ studies of rip currents are often time-consuming and costly due to their spatiotemporal variability and dynamic nature [7] .Therefore, there is a growing need for novel approaches (such as the integration of acoustic systems and satellite-derived data alongside traditional field measurements) to enhance our understanding of the behavior of these coastal currents [8].

Previous investigations have highlighted the application of various indicators and methods for studying rip currents, which, despite their individual limitations, function as effective tools and ultimately complement one another [2][9].

These research tools are generally classified into seven main categories: (i) numerical simulations, (ii) coastal video monitoring, (iii) laboratory analyses, (iv) field measurements, (v) analytical methods, (vi) remote sensing and coastal image processing techniques, and (vii) artificial intelligence techniques.

The first category—numerical simulations—has been widely utilized to explore a range of aspects, including the influence of coastal morphological features and seabed parameters on the characteristics of rip currents in a given region [1]. Other aspects addressed through numerical modeling include hydrodynamic properties, tidal variations, wave climate, rip current intensity and distribution, as well as morphodynamic changes and sediment transport mechanisms within rip channels [10] [11][12].

The second category, known as coastal video monitoring, has been deployed in various locations to investigate rip currents and their impacts on shoreline dynamics. These coastal monitoring techniques focus on the mechanisms of wave-induced currents, their behavior, and movement patterns while also addressing issues related to coastal erosion [13][14].

The third category, laboratory observations, serves as a valuable approach for analyzing the three-dimensional structure of rip currents [15][16], establishing causal relationships between hydrodynamic and morphodynamic variables, and understanding the dynamics of rip current systems in the nearshore region [17]. Primarily, laboratory investigations are employed to examine the formation and behavior of rip currents, the influence of various environmental factors on their development, and the conditions that affect their mobility [18]. Field observations play an indispensable role in complementing and validating rip current research. These studies provide valuable data on beach topography, bathymetry, shoreline changes, and the hydrodynamic characteristics governing the surf zone—such as incoming wave features—which are essential for understanding rip current generation mechanisms [19][20][21]. Field studies also assist in identifying spatial and temporal variations in shorelines and sediment bars, both of which are closely linked to rip current formation [22].

Additionally, field investigations facilitate the collection of sediment samples, enabling analysis of sediment transport patterns associated with rip currents [23][24].

Furthermore, field observations offer a critical opportunity to validate numerical models used to simulate rip currents [22][2][25] .Comparing numerical modeling results with field data yields a more comprehensive understanding of rip current events and their associated hazards, ultimately leading to improved safety measures for swimmers and more effective coastal management strategies [26] [6].

The fifth category, referred to as analytical models, encompasses the study of rip current formation patterns [27], wave–current interactions [28], and the prediction of various system characteristics such as current velocity [29] and rip spacing [30].These studies, in conjunction with laboratory and field observations, contribute to resolving existing uncertainties in nearshore hydrodynamic phenomena.

The sixth category, remote sensing and image processing techniques, provides valuable insights into the behavior of rip currents and assists in their identification and visualization [31][32].

In addition to these methods, the emergence of machine learning and artificial intelligence as the seventh category—either used independently or in combination with image processing techniques—represents a growing trend that facilitates automated rip current detection. These advanced approaches are capable of analyzing large volumes of imagery and detecting patterns and trends that may otherwise go unnoticed due to the transient nature of rip currents, which often hampers detection using conventional techniques [33][34].

In this context, over the past few decades, a considerable body of research within coastal engineering and management has focused on identifying the features and locations of rip currents using image processing, remote sensing, and AI techniques—an effort largely driven by the complex nature of these currents. Accordingly, the present study aims to examine the challenges and assess the strengths and limitations of various approaches based on image processing and remote sensing in rip current studies. As evident from the existing literature, despite the emergence of AI frameworks and their undeniable advantages, prior reviews remain limited in scope and lack in-depth analysis, which may hinder a comprehensive understanding of the associated limitations and research gaps. Thus, this study provides significant support for researchers in identifying suitable strategies tailored to the specific challenges of each approach and advancing the objectives of future investigations. The structure of this paper is as follows: Section 2 presents the materials and methods, including an overview of remote sensing and image processing tools, as well as the search strategy. Section 3 provides a comparative analysis of the extracted results, including literature synthesis, key findings, and thematic classifications. Finally, Section 4 concludes with a summary of the main outcomes of the study.

2. Data and Methods

2.1. Remote Sensing Tools

Remote sensing tools have long been recognized as complementary, highly efficient, and cost-effective means for investigating coastal phenomena, particularly in monitoring transient coastal events [35].

When selecting remote sensing data, it is essential to consider their classification based on spatial scale—namely, global, regional, and local.

Global-scale remote sensing data are used for large-scale applications. These include datasets derived from various meteorological satellites employed for weather analysis, forecasting, and disaster prevention.

Regional-scale remote sensing data are typically obtained from medium-resolution imagery. Notable examples include data from MODIS and Landsat satellites, which are commonly used for monitoring the surface features of seas and oceans. Regional data are also valuable for macroscopic assessments of environmental changes in coastal areas.

Local-scale satellites, on the other hand, are primarily utilized for monitoring smaller spatial extents where higher spatial and spectral resolutions are required. Among the most prominent local-scale remote sensing tools are the WorldView satellite series and Unmanned Aerial Vehicles (UAVs). Accordingly, the selection of appropriate remote sensing imagery depends on the specific characteristics of the coastal features under investigation. Given that rip currents are small-scale and short-lived phenomena, the use of high-resolution imagery is highly recommended for their detection and analysis [36][37] (Table 1)

Remote sensing tools used for the study and detection of rip currents can be categorized into several groups. The first category includes permanent stations and Surf Cam video imagery, which consists of video cameras installed along the shoreline. These systems are designed to provide and collect real-time visual information on coastal and ocean conditions for both coastal residents and researchers. Such remote monitoring tools offer broad spatial coverage of data and enable quantitative measurement of coastal morphodynamic phenomena, tracking of water movement, and analysis of current behavior over time [38][39]. The second category comprises Remotely Piloted Aircraft Systems (RPAS) and Unmanned Aerial Vehicles (UAVs). These technologies, known as Unmanned Aerial Vehicle Remote Sensing (UAVRS), have made monitoring of rip current systems more accessible, cost-effective, and scalable across most parts of the world using aerial photography and surface observation [40]. These video-based methods operate through advanced techniques such as optical flow estimation, offshore direction calculation, and temporal data fusion to analyze and interpret rip current dynamics [41][31].

The third category includes satellites and marine radar systems, which can also be employed for rip current analysis. Among these are X-band radar systems, which, through specialized algorithms, are capable of estimating the location, shape, size, and speed of rip currents, as well as their seasonal variations—factors that are often difficult to measure using traditional field-based observation tools [42][32]. In addition, High-Frequency (HF) radar systems are widely used for continuous monitoring of oceanic waves and currents under various environmental conditions [43]. HF radar systems, such as CODAR SeaSonde and WERA, can measure coastal ocean currents and wave patterns by providing radial current measurements and return signal variations across both spatial and temporal domains. Spaceborne Synthetic Aperture Radars (SARs), such as those on ENVISAT, RADARSAT-2, ALOS, COSMO-SkyMed, and TerraSAR-X, are capable of providing high-resolution Earth surface imagery and are highly effective for rip current studies. These satellites operate by transmitting microwave pulses, which allow them to function independently of daylight and cloud cover [44][45]. Each of these options has its specific advantages and disadvantages, which are thoroughly analyzed and evaluated in this study, along with the challenges and limitations of each method.

Table 1. Specifications of commonly used remote sensing satellites for studying rip currents

Satellite Type	Satellites and Sensors	Launch Date	Spatial Resolution (m)	Spectral Resolution Band	Temporal Resolution (Day)
Radar Satellites	Sentinel-1	1978.10	825	6	6
	RADARSAT-2	2007.12	1	1(X-band)	A few days to a few weeks
	TerraSAR-X	2007.6	Up to 1 meter and even better	1(C-band)	A few days to a few weeks
Optical Satellites	Landsat satellites (Landsat 7 ETM+, Landsat 4-5 TM)	1984-2020	30	5	16
	MODIS	1999/2	250-500-1000	9	0.5
	Landsat 8 OLI	2013.2	30	7	16
	Sentinel-2	2A-2015.6 2B-2017.3	10-60	13	5(combined)
Altimeter Satellites	Sentinel-3	3A-2016.2 3B-2018.4	300-1000	8	27

2.2. Field and In-situ Data

In-situ data used for monitoring rip currents are essential for measuring various factors, including current velocities, wave characteristics, wind, and the circulation of the nearshore tidal area. They also help in determining sediment characteristics and the morphodynamic conditions of the coast, such as measuring the slope of different sections of the shore and mapping the bathymetry of channels. These measurements are obtained through various methods, such as Acoustic Doppler Current Profilers (ADCPs), GPS drifters, buoys, wave gauges, and coastal monitoring systems [46][47][48].

These in-situ studies, while examining the behavior of water movement, also enable the detection of rip currents in situations where other methods may fail [32]. Moreover, these data serve as real-time information for the studied area at any specific time and are used to evaluate remote sensing data, as well as to assess the accuracy of the location of current channels [49]. In-situ data also provide general information about the current conditions of the coastal region, including the state of the shore, substrate composition, and other physical water features, which are essential for predicting changes in the rip current system over time.

Furthermore, in-situ data collected from sources such as buoy records, tidal gauges, and backscatter profilers can be utilized to estimate coastal erosion patterns, wave-breaking patterns, and the stability of shoreline features [37]. It is worth noting that a combination of in-situ measurements and remote sensing data provides a more comprehensive understanding of rip current dynamics, enabling the identification of rip current systems and their behavioral changes under varying wave and substrate conditions that may not be captured by in-situ sensors [36].

2.3. Image Processing Methods

The general steps in image processing for rip current detection include Image Acquisition, Image Pre-processing, Feature Extraction, Detection and Classification, and Post-processing and Refinement (Figure 1). In the first step, Image Acquisition, rip current images are obtained from various sources using remote sensing tools. In this phase, special attention should be paid to imaging conditions (image quality, viewing angle, time of acquisition, and weather conditions).

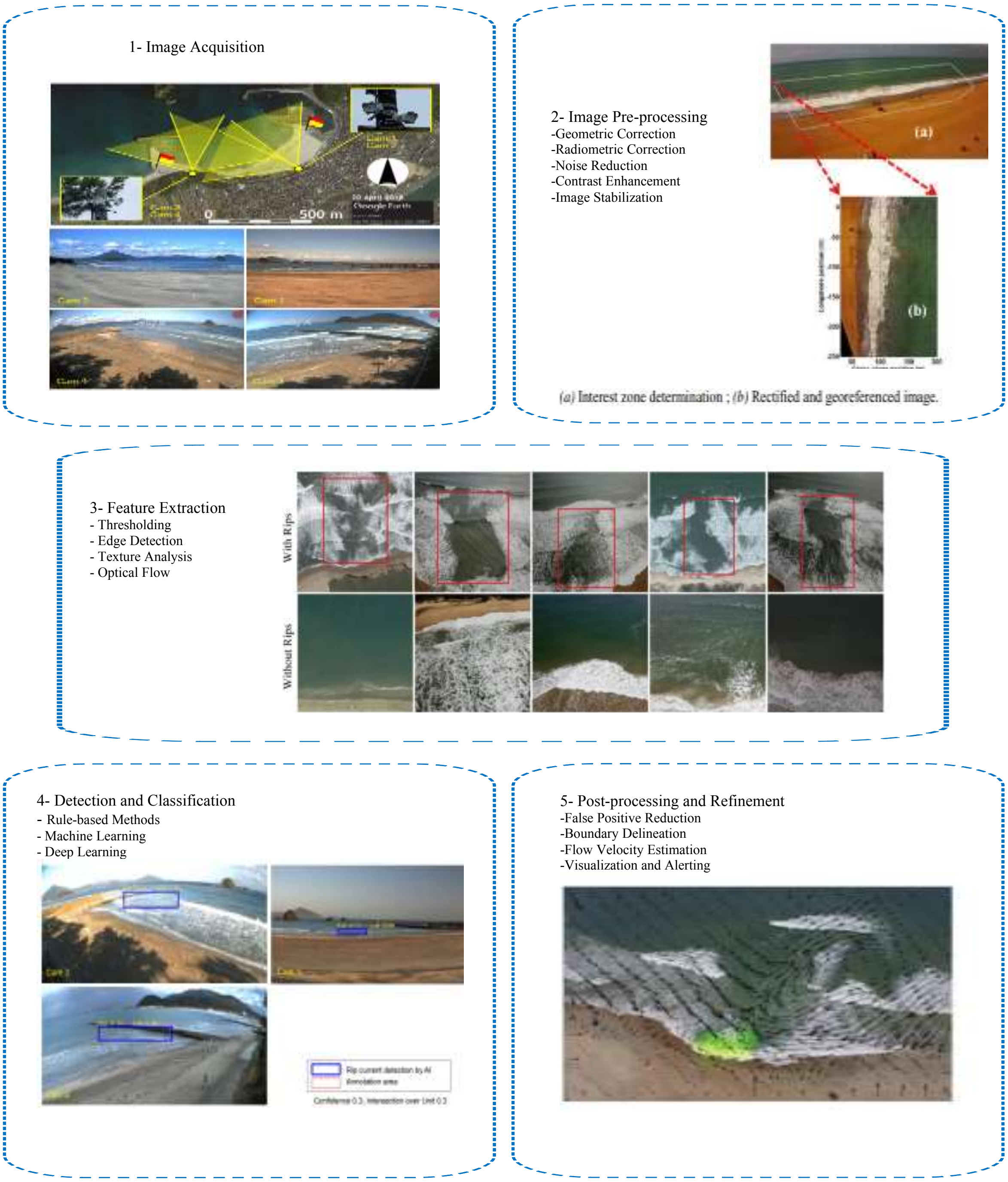

Figure 1. Image processing steps for ripping current studies [50]

In the Image Pre-processing stage, several operations are performed, including Geometric Correction, Radiometric Correction, Noise Reduction, Contrast Enhancement, and Image Stabilization to optimize results and improve the accuracy of the analysis. The next step, Feature Extraction, involves identifying rip current features in the form of visual patterns using suitable techniques such as Threshold (separating regions with specific brightness or color intensities), Edge Detection (identifying boundaries between regions with distinct visual features), Texture Analysis (examining patterns of intensity variations in a region to detect different water textures), Optical Flow Analysis (estimating the speed and direction of pixel motion in a video sequence), and finally, the use of Machine Learning algorithms plays a key role in automatic feature extraction and the development of rip current warning systems.

The following stage is Detection and Classification. Various methods are available for classifying rip currents, including Rule-based Methods, Machine Learning, and Deep Learning approaches. The detection of rip currents is based on the analysis of extracted features, where algorithms determine whether a rip current exists in the image and identify its location.

The final image processing step for rip current detection is Post-processing and Refinement. This stage includes False Positive Reduction, Boundary Delineation, Flow Velocity Estimation, and finally, Visualization and Alerting [51][52] .

A review of the available literature and scientific sources indicates that image processing methods for rip current detection are typically categorized into four groups: Traditional Image Processing, which involves classical image processing methods such as spatial filters, texture analysis, and visual feature extraction; Computer Vision, which includes the use of advanced computer vision algorithms; AI & Machine Learning, which involves employing Convolutional Neural Networks (CNNs), deep learning, and models such as YOLO and Grad-CAM for automatic rip current detection; and finally, Hybrid Models, which combine image processing methods with physical models or flow analysis.

2.4. Search Strategy

In this study, since the goal is to review the literature on research conducted on image processing and remote sensing techniques for the study of rip currents in recent years, including 41 articles (published between 2014 and 2023), both database search and snowball search methods were employed.

In the database search method, reputable databases were used to search for relevant articles from established scientific journals. In some cases, the snowball search method was utilized by referring to the sources of the identified articles. In the second approach, starting with a small set of related articles, the search was extended by examining their references and articles citing them.

This process enabled a comprehensive review of the literature and prior research in the field of study. Boolean operators were employed in the database search to refine the queries and obtain more relevant results. This allowed the search results to be narrowed down and the desired information to be presented more efficiently (Table 2).

Table 2. Selected Keywords in the Database Search Method

Search terms
(“rip currents detection” OR “rip currents monitoring” OR “rip current observation” OR “rip current forecasting”) AND (“image processing” OR “coastal remote sensing” OR “marine radar”) AND (“artificial intelligence” OR “machine learning” OR “deep learning” OR “convolutional neural network”)

3. Comparative Analysis/ Trends in Literature

Given the substantial number of studies in the reviewed literature, a concise summary of the main findings and applied techniques—categorized by author names and accompanied by specific methodological details—is provided in Table 3.

A brief examination of this table reveals that the most commonly utilized approach in image processing methods is the hybrid image processing technique, accounting for 78% (32 out of 41) of the reviewed studies. Among these hybrid approaches, several studies—such as that of Rampal et al. (2021)—focus on models integrating classical image processing techniques with artificial intelligence [53] .

Other studies, including those conducted by Mori et al. (2022) and de Silva et al. (2023), propose models that combine machine learning algorithms with flow analysis techniques [34][48]. Additionally, some research, such as the studies by Ishikawa et al. (2023) and Islam et al. (2022), explore hybrid models based on multi-source data integration—combining coastal surveillance camera data, satellite imagery, and drone images—to train machine learning models for rip current detection [52][50]. Furthermore, certain studies, such as the one by Haroon Rashid et al. (2023), fall into the category of models that integrate deep learning techniques with physical features, utilizing YOLO-V3 as an object detection framework [54].

Table 3. A summary of the main findings and applied techniques in various studies.

	Reference	Image processing	Used techniques	Type of study	Limitations of the study
1	Haller et al. (2014)	Hybrid method	- / Marine radar (X-band nautical)	Visualization and Tracking	- Limitation of generalizing the findings to other regions - Temporal limitations, with data being provided only as a 10-day average - Neglect of non-visual factors influencing current formation - Limitation of radar application in specific environmental conditions - Lack of investigation into the potential impacts of rip currents on swimmers - Absence of detailed information on the vertical structure currents - Spatial resolution limitations of marine radar
2	Sembiring et al. (2014)	Hybrid method	- / Coastal video imaging systems-Argus station (Argus video)	Bathymetry	- Limitation of generalizing the findings to other regions - Neglect of non-visual indicators and the potential uncertainties associated with video-based depth measurement technique - Accuracy of video-based measurements is dependent on environmental factors
3	. Hwang et al. (2014)	Traditional Image Processing	- / Traditional coastal video imaging systems -CCTV cameras (CCTV images)	Detection	- Inability to generalize the findings to other locations or beaches - Lack of suitable data quality due to the poor quality of CCTV images - Absence of discussion on potential challenges in practical beach management - Lack of further validation and testing of the developed method in diverse coastal environments
4	Bogle et al. (2014)	Traditional Image Processing	- / Traditional coastal video imaging systems (rectified image)	Observation and monitoring	- Inability to determine the exact location of sediment bars -Temporal and spatial limitations in recording current features
5	Yoon et al. (2014)	Hybrid method	- / Traditional coastal video imaging systems -CCTV cameras (CCTV images)	Tracking and locating	- Limitations in generalizing the findings - Limitations in video analysis and the potential for errors - A limited number of data points for velocity measurements - Limited information on the bathymetry of the underwater topography - Insufficient information regarding the characteristics and location of the drowning swimmers
6	Shin et al. (2014)	Hybrid method	Traditional coastal video imaging systems	Tracking and monitoring	-Limitation in estimating long-term morphological changes due to low resolution -Limitation in accurate measurement and the need for multi-image monitoring -Limitation in the generalizability of findings to other areas -Lack of investigation into the dynamic mechanisms of sediment transport
7	Wilson et al. (2014)	Hybrid method	electro-optical, infrared, and radar techniques (optical imagery, Argus time-exposed image, Infrared Particle Image)	Bathymetry	- Limitations in managing spurious long-range spatial correlations in the EnKF method - Limitation of the system's ability to generate long decorrelation lengths - Challenges in interpreting negative depths in specific locations
8	Hally-Rosendahl et al. (2015)	Hybrid method	- / A small plane (equipped with the multispectral camera system)	Tracking	-Lack of generalizability of findings to other coastal locations -Ignoring the long-term behavior trends of currents -Reliance on dye tracer measurements and lack of investigation into sediment transport processes -Uncertainty in estimating current velocities -Neglecting the impact of wave conditions on current dynamics
9	Sun et al. (2015)	Hybrid method	- / Coastal video imaging systems (UAV &Optical flow video-based technique)	Detection	-Lack of a detailed analysis of accuracy or false positive/negative rates -Potential limitations or considerations related to the use of drone technology -No discussion of the scalability of the proposed framework for large-scale implementation -Potential challenges in deploying drones for flow detection in various environments -Lack of comparison or evaluation of the proposed framework with other methods
10	Li et al. (2016)	Hybrid method	- / Remote sensing images (Not mentioned)	visually observe and analyze	-Inability to apply the study results to other regions -Limitations of the proposed method due to its reliance on the surf zone model -Failure to consider temporal variations in coastal hazards and rip current conditions -Lack of long-term observations to validate the proposed method
11	Scott et al. (2016)	Hybrid method	- / Remote sensing cameras was installed on the cliff top (plan-view timex images)	Tracking	-Limitation in generalizing the findings to other coastal areas -Lack of investigation of the effect of groin spacing and permeability on rip current dynamics -Lack of investigation of long-term changes in rip current behavior -Focus of the analysis on a specific range of wave conditions
12	Benassai et al. (2017)	Hybrid method	UAV (Unmanned aerial vehicle) & RPAS (Remotely Piloted Aircraft Systems)- Google earth images	Detection	-Inability to generalize the findings to other coastal areas -Uncertainties in accurately representing real-world conditions -Neglecting the impact of seasonal variations on rip current formation -Specific operational conditions (daylight, altitude limitations, etc.) in RPAS investigations -Neglecting the potential impact of human activities on current dynamic
13	Derian et al. (2017)	Hybrid method	- / UAV (Unmanned aerial vehicle) & optical flow	detection and monitoring	-Challenges in image quality and resolution in optical flow methods based on wavelets -Reduction in accuracy in videos due to raindrops or dust on the camera housing -Reduction in estimation accuracy due to the larger pixel size of images compared to the resolution of the modified grid -Limitations of comparison due to the limitations of comparing OF criteria with the results of acoustic Doppler velocimetry -Computational limitations of the proposed algorithm in real-time applications
14	Leatherman et al. (2017)	Hybrid method	- / Quadcopter drone	Detection	-Inability to generalize findings to coasts with different wave climatic -Lack of coverage of the impact of seasonal changes on the rip current system -Absence of discussion on specific human interventions
15	Radermacher et al. (2018)	Hybrid method	- / Coastal video imaging systems (UAV)	Bathymetry	-Limitations in generalizing findings to other locations and times -Inherent uncertainties in the depth inversion algorithm used for remote sensing bathymetry -Neglect of the dynamics of important near-shore processes or hydrodynamical processes -Limitations in the analysis due to camera resolution, georeferencing quality, and changes in wave climatic -Need for further validation and sensitivity analyses in diverse coastal settings
16	Gallop et al. (2018)	Hybrid method	- / Coastal video imaging systems-'Cam-Era' video system (time-exposure image, and Google Earth) & bathymetry observations (LiDAR)	Bathymetry	-Limitation of generalizations to other coasts -Neglect of the full complexity of coastal rip current zone dynamics and rip current behavior -Lack of investigation of wave variability at long time scales due to the limited study time -Neglect of the impact of human factors, such as beach user behavior or lifeguard interventions -Lack of consideration of the impact of seasonal changes or storm events on circulation patterns
17	Sridevi et al. (2019)	Hybrid method	- / High-resolution satellite imageries (ncluding Pleiades, Digital globe, Airbus, and Google Earth)	analyzing	-Limitation in generalizing results to other coastal areas -Recording rip current events over a limited time period rather than a long-term period -Insufficient information regarding the demographic characteristics of drowning victims or the exact circumstances surrounding each drowning event. -Lack of discuss the potential impact of human factors or safety measures on beaches and their influence on the results. -High cost of high-resolution satellite imagery -Dependence on weather, cloud cover conditions, solar radiance, and other meteorological conditions and their impact on the quality of remote sensing images.
18	Pujianiki et al. (2020)	Hybrid method	- / Coastal video imaging systems (UAV)	Visualization and Tracking	-Limitation in generalizing the findings to other rip current-prone areas due to the focus on a specific location. -Lack of use of complementary techniques such as in-situ measurements or numerical modeling for analysis, and reliance solely on aerial and drone imagery. -Lack of discussion of the effectiveness and practical implementation of these beach rip current warning strategies. -Lack of consideration of potential errors associated with placing ground control points (GCPs), measurement accuracy, or data integration. -Lack of assessing the feasibility of using drones in broader coastal safety initiatives in future research endeavors.
19	McGill et al. (2021)	Hybrid method	- / Coastal video imaging systems (UAV)	detection	-The accuracy of rip current detection and the reduction of backwash detection with false positives are influenced by changes in the surfcam camera angles

					-Challenges related to camera placement and limitations in controlling the placement of surfcam cameras -False detections (false positives), particularly including swimmers, surfers, as common sources of error in rip current identification -Limitations in image correction and the use of uncorrected images -Limitations in calibration methods due to the subjective nature of visual observations for calibration and validation, instead of in-situ instruments
20	Carpi et al. (2021)	Hybrid method	- / Coastal video imaging systems (UAV)	monitoring	-Limitation of high-resolution bathymetry data -Influence of rip current erosive capacity on near-shore bed grain size and bathymetry, and its impact on the accuracy of findings -Limitation of rip current visibility in the visual monitoring system due to boundary conditions such as seabed, waves, and sunlight -Limitation of collecting field data for rip currents due to the dynamic nature of the surf zone
21	Kim et al. (2021)	Hybrid method	- / Landsat satellites (Google Earth images), Drone	Tracking	-Limitations of GPS drifters due to low accuracy and being trapped in the surf zone -Limitation of the study scope and available resources for data collection and analysis -Limitation of generalizing the findings to other coastal areas with different characteristics -Decrease in the accuracy of the dye-tracking method under the influence of environmental factors such as wind speed, water turbidity, and dye dispersion -Lack of discussion on potential discrepancies or error sources between the two methods of dye tracking and numerical simulations
22	Fatchurohman et al. (2021)	Hybrid method	- / Coastal video imaging systems (UAV)	Tracking & monitoring	-Limitation of generalizing the findings to other coastal areas -Lack of a comprehensive investigation into the complexity of rip current dynamics due to the reliance on fluorescent dye and drone technology -Neglecting additional factors influencing rip current formation, such as seasonal variations, wave patterns, and coastal morphology -Limitations of the fluorescent dye method, including dilution and dispersion in natural waters -Lack of investigation into the impact of human factors influencing rip current incidents, such as beachgoer behavior and safety awareness levels
23	Zhang et al. (2021)	Hybrid method	- / UAV (Unmanned aerial vehicle) & Aerial and shore-based optical cameras -Google earth images	Tracking & bathymetry & Identification	-Limitations in accurately predicting the timing and location of rip currents due to the highly variable spatiotemporal nature of these phenomena -Limitations in considering the full extent of rip currents in field studies -Limitations in the effectiveness of remote sensing tools, such as optical cameras and LiDAR, in accurately capturing the dynamics of rip current
24	Marchesiello et al. (2021)	Hybrid method	- / Coastal video imaging systems (UAV)	Tracking & monitoring	-Limitation of generalizing the findings to other coastal areas -Limitation of computational resources required for 3D wave-resolving models -Creation of a level of uncertainty in model results due to model simplifications and assumptions -Potential sensitivity to specific model settings and their impact on results -Necessity for further validation of findings against real-world data and scenarios
25	Hong et al. (2021)	Hybrid method	- / Coastal video imaging systems (UAV)	Tracking	-Focus on short-term simulations and neglect factors such as the long-term evolution of sedimentary barriers, irregular waves, and tides -Neglecting sediment transport in modeling to provide a more comprehensive understanding of rip current dynamics -Limitations arising from not considering the impact of long-term observations on specific sections of the coastline to provide more statistical data -Limitation arising from not examining the combination of empirical formulas or probabilistic models
26	Xue et al. (2021)	Traditional Image Processing	- / HISEA-1, the first C-band SAR small satellite	Observation and monitoring	-Incomplete calibration due to the HISEA-1 being in the startup phase and the image processing plugin of HISEA-1 still under development. -Lack of a comprehensive analysis of all the features that can be identified using SAR images
27	Rodríguez-Padilla et al. (2021)	Hybrid method	- / Coastal video imaging systems (Optical flow video-based technique)	detection	-Limitations in the accuracy of flow velocity estimation using the optical flow technique -Limitations arising from the fixed position of the camera on the coast and the lack of consideration of the variability of the coastal rip current circulation -The inability to generalize the findings due to the study's focus on high-energy wave conditions and the lack of consideration of the optical flow method under different wave energy regimes -Potential limitations in the accuracy and uncertainty of in-situ drifter results
28	Anderson et al. (2021)	Hybrid method	- / Coastal video imaging systems -Argus station (Argus image- high-resolution optical cameras- Optical flow video-based technique)	Detection & Identification - Tracking & monitoring	-The need to develop and improve filtering techniques presented with in-situ observations -Optimization of selected parameters in the WAMFlow technique based on field measurements -Limitations in the selected optical tracking algorithm in WAMFlow, for example, the inability to identify sharp edges -The challenging nature of directly comparing velocities provided by drifters with remotely sensed or in-situ fixed current meters -Limitations arising from changes in environmental conditions, such as tidal level and offshore waves, for longer deployment periods of drifters compared to image recordings
29	Borra et al. (2022)	Hybrid method	- / Coastal video imaging systems (marine radar-timex image- GNSS drifters)	Identification & monitorization	-Lack of continuous or sufficient video image data -Limited generalizability of the findings to other coastal regions -No discussion of the specific remote sensing tool used for satellite image analysis, and its impact on the reproducibility and comparison of the study with other research efforts -Lack of providing consistent and reliable data over long periods due to the temporary nature of the video camera setup -Failure to examine the potential effects of human interventions or coastal structures on rip current dynamics
30	Pitman et al. (2016)	Traditional Image Processing	- / Coastal video imaging systems (marine radar-timex image)	Detection	-Limitations in accurately identifying rip currents due to significant differences in detections based on original and synthetic images -Insufficient prediction of rip channel occurrence due to oversimplification of morphology in images in the proposed method -Limitations in the accuracy of results due to significant noise in the original image
31	Maryan et al. (2019)	AI & Machine Learning	Machin learning -SVM, CNN / -	Detection	-Limitation of generalizations to other types of tasks Object detection due to focusing on rip channel detection -The need to train convolutional neural networks on a large dataset for suitable results -Oversimplification of the model selection process due to comparing datasets to determine the most effective input type for each model -Lack of comprehensive analysis of all potential factors affecting algorithm performance -Lack of in-depth discussion of practical concepts, applications, or challenges of deployment in the real world
32	Ellenson et al. (2020)	AI & Machine Learning	Machin learning (CNN) / coastal video imaging systems (marine radar-Argus daytimexposure imagery)	Visualization & detection	-Limitation of generalizing results directly to other locations -Lack of investigation into the impact of different image pre-processing techniques on the performance of the CNN model -Limitation of the CNN model's performance under the influence of the quality and resolution of daily Argos exposure images as input -Lack of investigation into the potential impact of environmental factors, such as weather conditions or seasonal variations, on the model's classification accuracy -Lack of comparison of the CNN model's performance with other machine learning algorithms or traditional image processing techniques -Lack of attention to the computational requirements and scalability of the CNN model for large-scale applications -Lack of a comprehensive analysis of limitations and potential sources of error in the process of classifying coastal states using CNN
33	de Silva et al. (2021)	AI & Machine Learning	Faster R-CNN / ground-based imaging (stationary cameras	Detection	-Limitation of the dataset used for training and testing the model and overestimation of results in real-world scenarios

			such as CCTV or web cameras) & Google EarthTM		-Need to collect more diverse samples of visual representations of rip currents in future work -Need to evaluate and explore metrics that incorporate a temporal dimension to improve model training and performance -Creating a challenge in comparing model performance with previous works due to the lack of public datasets to validate results -Lack of using transfer learning due to the unavailability of pre-trained deep learning models in similar domains to improve model performance
34	Rampal et al. (2022)	Hybrid method	Deep learning (technique Grad-CAM) / High-resolution aerial imagery from Google Earth	detection and localization	-Limitation of generalizing the model to diverse coastal environments and marine conditions -Limitation of the complexity of resolving the amorphous structure with artificial intelligence -Limitation in terms of robustness and applicability in the real world -Limitation of the algorithm's applicability to other types of data sources or monitoring systems
35	Mori et al. (2022)	Hybrid method	Machine learning method - Timex (Time-exposure images) and Faster RCNN / Coastal video imaging systems(surfcams)	Detection	-Ignoring other detection techniques or factors affecting rip currents and focusing on flow visualization methods - Limitations of the direct application of flow visualization methods -Limitations of the applicability of methods for specific video metrics due to the data required for analysis, including video quality, stability, and duration -The challenging nature of detecting weak rip currents due to low flow velocity -The inherent limitations of rip current detection methods due to the complexity of defining clear boundaries and temporal bounds
36	Zhu et al. (2022)	AI & Machine Learning	(YOLO-Rip)-Deep learning(joint dilated convolutional) / -	Detection	-Limitation of generalizing the model to various rip current features due to the focus on improving the accuracy of rip current detection using the YOLO-Rip model -Lack of discussion of potential limitations in real-world deployment scenarios, such as different environmental conditions or complex backgrounds -Lack of comparison of the YOLO-Rip model with a wider range of existing advanced models for rip current detection -Failure to address the computational resources required for training and deploying the model -Lack of attention to potential challenges related to data collection, preprocessing, or interpretability of the YOLO-Rip model for real-world implementation
37	Islam et al. (2022)	Hybrid method	Deep learning and Machine Learning-- Machin learning (CNN) / Drone-shot images, bathymetric images, Google earth images	Detection	-Failure of the proposed approach (CNN and MLA) for images that do not match the training dataset -Lack of extensive investigation of various factors due to the focus on beach images, bathymetry images, and beach parameters -Limitation of the generalizability of results to different coastal conditions -Challenges in real-world scenarios when implementing data collection methods -Lack of a comprehensive analysis of the limitations and potential uncertainties of the proposed models and their practical application in coastal management -Lack of a comprehensive analysis of false positive and false negative rates of detection models and their impact on real-world practical application
38	Qi et al. (2023)	Hybrid method	(YOLOv5s model)-Deep learning(joint dilated convolutional) -Deep learning (joint expansion convolution JDC) /-	Detection	-Limitation of the applicability of the findings in scenarios with multiple scattered flow targets in a single image -Limitation in addressing real-world environmental interferences that affect detection accuracy -Limitation of generalizing the model to different coastal environments or different rip current conditions -Limitation of the real-time application of the improved model in coastal management scenarios in real-world rip current detection and warning systems
39	de Silva et al. (2023)	Hybrid method	(RipViz)-Deep learning-LSTM (Long Short-Term Memory) /-	analyzing and visualizing	-Challenges related to the difficulty of learning the behavior of machine learning algorithms, especially LSTM autoencoders, to detect abnormal trajectory sequences -Lack of information regarding the performance or accuracy of the RipViz method in detecting and visualizing rip current
40	Haroon Rashid et al. (2023)	AI & Machine Learning	(RipDet+) -Deep learning & Deep neural network /-	Detection	-Challenge of dealing with small training sample size and the unavailability of pre-trained models -Failure to increase performance with an increase in the number of warm-up epochs or the use of a relatively high fixed learning rate during training -Lack of investigation of ensemble techniques for RipDet -Limitations of using SGD and SGD with momentum instead of Adam for Rip current detection
41	Ishikawa et al. (2023)	Hybrid method	deep learning techniques (Tiny YOLO algorithm as the object detected) / web cameras placed strategically on the beach	Detection	-Limitation in detecting fully and accurately (with an AI model accuracy of 48%) rip currents by the AI model -Challenges related to changes in wave conditions and obstacles such as water droplets on the camera for accurate rip current detection -Limitation related to the need for new training data to improve the overall goal of the AI model and improve rip current detection

The results of this study, as illustrated in Figure 2, indicate that among the remote sensing techniques employed, aerial imaging accounts for the highest proportion of use (38.77%) and is regarded as one of the main and most widely applied methods in rip current studies. Satellite imagery ranks second, with a usage share of 24.48%. A review of relevant studies shows that one of the main reasons for the widespread application of aerial imaging in these studies is the higher spatial resolution of images captured using drones compared to satellite imagery [55][3]. This characteristic enables researchers to observe more detailed features of rip currents, such as wave patterns, breaking zones, and water level variations [1][56]. Moreover, operating aircraft or drones to capture aerial images offers significantly greater flexibility than other techniques [57], allowing for easy acquisition of images at various times and specific locations [58]. In addition, some aerial cameras are capable of collecting multispectral data, which can be used to extract further information about water properties. Compared to other methods such as LiDAR, aerial imaging is generally less expensive and more cost-effective [59]. Furthermore, findings from various studies demonstrate that aerial imagery can be integrated with data obtained from other sensors—such as radar and sonar—to generate a more comprehensive understanding of coastal environments where rip currents occur [60]. It is important to note, however, that the selection of an appropriate method for studying rip currents depends on various factors, including the research objective, available budget, access to equipment, and environmental conditions. Nonetheless, due to the aforementioned advantages, aerial imaging is recognized as one of the principals and most commonly used techniques in this field, with a usage share of 38.77%.

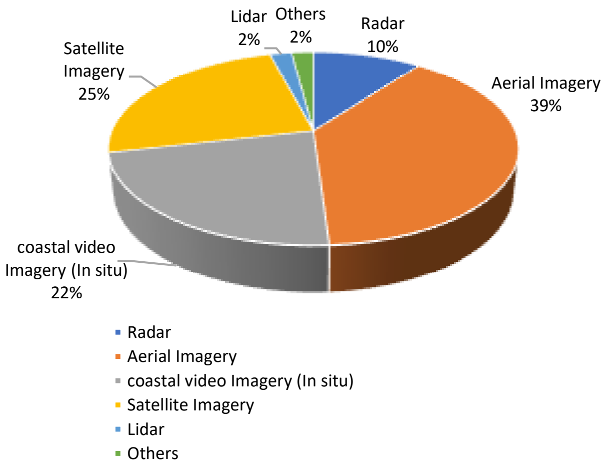

Figure 2. Categorization of percentage of used remote sensing technique for rip current studies.

A review of various studies on rip current research, as illustrated in Figure 3, reveals that Convolutional Neural Networks (CNNs), with a usage share of 33.33%, are the most widely used artificial intelligence method for image processing in rip current detection. There are several reasons for the widespread adoption of CNNs in this context, primarily related to the unique characteristics of these networks and the nature of rip current-related data. CNNs are specifically designed for image data processing, and in rip current studies, visual data—such as aerial imagery, satellite images, and marine videos—serve as the primary source of information. A review of relevant literature demonstrates that CNNs are highly capable of recognizing complex visual patterns, textures, and features present in such imagery [33][61][52].

One of the key advantages of CNNs lies in their ability to automatically extract significant features from data. This capability stems from their deep architecture, which allows them to learn multiple levels of feature abstraction. As a result, CNNs can identify more intricate patterns compared to other methods. Moreover, images of rip currents often contain noise and environmental variability, and CNNs, due to their strong generalization capabilities, are more robust to such noise and can detect rip currents with greater accuracy [33]. In addition, recent years have witnessed significant advancements in CNN technologies, along with the development of powerful software libraries such as TensorFlow and PyTorch, which have made their implementation more accessible for researchers. Following CNNs, the next most commonly used AI tools in rip current studies are Faster R-CNN and Tiny-YOLOv3 & RipDet^{+}, each accounting for 16.66% of usage. These models are designed for object detection in images and have been adapted for rip current detection as well [62][54][50]. Nevertheless, due to their greater flexibility and superior ability to learn complex features, CNNs remain the most popular choice among researchers [63].

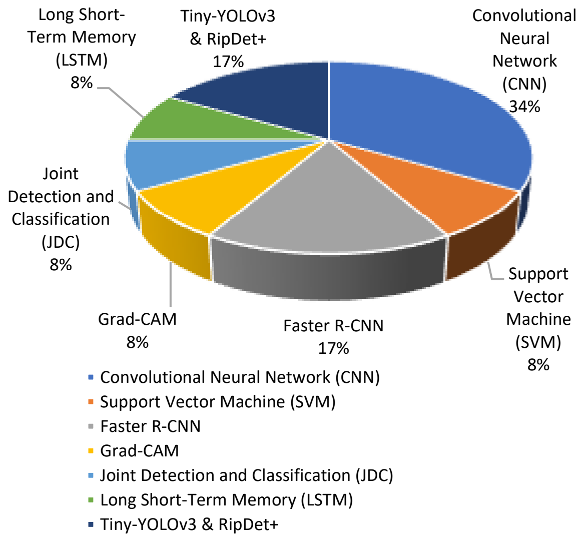

Figure 3. Categorization of percentage of used AI technique for rip current studies.

The results also indicate that among various imaging techniques—namely Radar Imagery, Optical Imagery, Lidar Imagery, and Thermal Imagery—optical imagery holds the highest share of application (39.81%) in remote sensing studies of rip currents (Figure 4). This widespread use can be attributed to several advantages of optical imagery, including high spatial resolution for capturing fine details of the water surface, waves, and flow patterns; relatively low cost; ease of interpretation; and accessibility of the imagery [64][65].

Moreover, the limitations of other imaging methods further reinforce the preference for optical imagery. For instance, although radar imaging, with a usage share of 13.95%, is capable of capturing data in adverse weather conditions and at night, literature reviews indicate that its resolution is generally lower than that of optical imagery. Additionally, radar image interpretation is more complex due to the influence of factors such as incidence angle, polarization, and surface roughness [36][31]. Lidar imagery, representing 2.32% of usage, enables precise measurement of water surface elevation, yet its application is limited due to high equipment and data processing costs [32][66][67] .

Moreover, the limited penetration of laser signals in water restricts its ability to study subsurface layers. Similarly, thermal imagery, with a comparable share to Lidar, is useful for detecting temperature differences on the water surface but is less suitable for high-resolution surface current analysis.

As illustrated in Figure 4, within the optical imagery category, visible imagery accounts for a significantly larger share compared to near-infrared (NIR) imagery. This preference is due to the considerable advantages of visible imaging. Since 2014, advancements in digital camera technology have led to increased image resolution, reduced noise, and improved performance under various coastal environmental conditions [68].

Furthermore, the development of image processing software has enabled the extraction of quantitative information such as current velocity, flow direction, and wave height. The more limited use of near-infrared imagery stems from several drawbacks, including restricted water penetration, the need for specialized equipment, and the complexity of interpreting NIR images due to the influence of variables such as temperature, humidity, and surface material composition. These factors have led to the broader use of visible imagery in rip current studies.

It is also worth noting that the selection of X-band radar imagery over other radar technologies, such as Synthetic Aperture Radar (SAR) in rip current studies, is due to several key advantages. X-band radar provides higher spatial resolution because of its shorter wavelength, which enables the capture of more detailed images of water surfaces and flow patterns. Additionally, X-band radar is highly sensitive to small changes on the water surface, making it especially suitable for detecting phenomena such as small waves, foam, and rip current-induced surface variations. Its limited penetration into water confines the imagery to surface-level features, which is beneficial for studying surface currents. Moreover, X-band radars are generally more cost-effective than SAR systems, making them more accessible for widespread research applications [32]. Given these benefits and the limitations of SAR, the use of X-band radar in rip current studies has significantly increased since 2014.

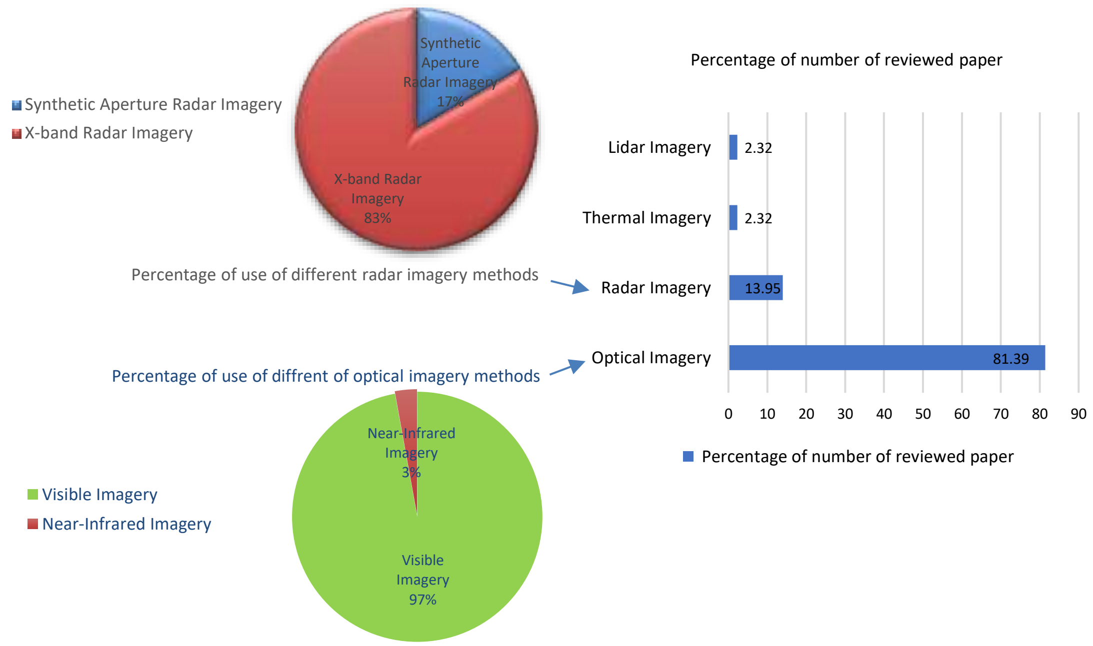

Figure 4. Categorization of Percentage of number of reviewed papers, based on Remote sensing imaging methods used for rip current studies.

The analysis of various sources, as illustrated in Figure 5, reveals that although rip current detection (38%) plays a crucial role as the first step in managing the risks associated with this phenomenon, tracking and continuous monitoring of rip currents are also of significant importance. However, there are several reasons why tracking and monitoring have received less attention than detection in recent years [69]. Other research objectives, including depth estimation, visual representation, and data analysis, are also pursued to enhance understanding and promote the practical application of research findings [70][71][13]. One of the main reasons for the predominant focus on rip current detection (with a 38% share) is the fact that rip currents are among the most hazardous marine phenomena, claiming numerous lives each year. Early detection of these currents can greatly contribute to saving the lives of swimmers and boaters [40]. Moreover, rip currents are often not visually apparent and may be hidden beneath the surface or obscured by strong wave activity, rendering traditional shoreline surveillance methods insufficient for preventing accidents [72][14][73].

As a result, recent advancements in remote sensing—particularly high-resolution satellite imagery and radar data—have facilitated more accurate and timely detection of rip currents. Furthermore, machine learning and artificial intelligence algorithms are capable of analyzing vast amounts of data and identifying complex patterns within satellite images. Consequently, accurate and timely detection of rip currents supports the enhancement of early warning systems and coastal safety management [74] .In addition, information obtained through detection efforts can be utilized in numerical modeling of coastal currents, designing coastal structures, and planning recreational activities along the shore [75][53]. In contrast, the relatively lower focus on rip current tracking (22%) and monitoring (18%) can be attributed to the technical and operational challenges associated with these systems. Rip currents are highly dynamic and variable phenomena, influenced by multiple factors such as tides, winds, and coastal morphology. Accurately and continuously tracking these currents requires advanced monitoring systems and sophisticated algorithms [76][25]. Moreover, establishing and maintaining extensive monitoring systems along long and dispersed coastlines is highly costly. Remote sensing data and other observation methods may not always provide the resolution and accuracy necessary for precise rip current tracking. Additionally, rip currents can change direction and intensity rapidly, requiring monitoring systems to be capable of detecting these swift variations. All these factors—combined with the fact that evaluating the effectiveness of tracking and monitoring methods requires long-term, high-quality datasets—have resulted in comparatively less attention being paid to tracking and monitoring in rip current research compared to detection efforts [39].

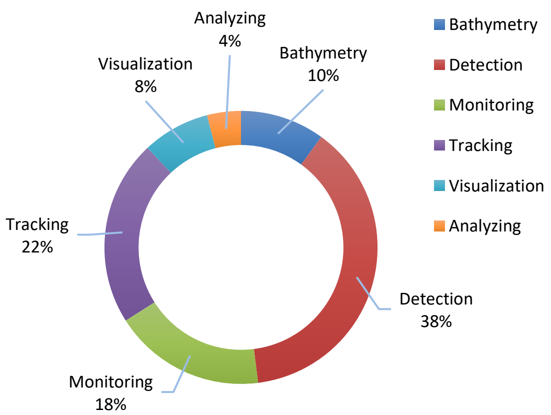

Figure 5. Categorization of percentage of study type for rip current studies.

4. Research Gaps and Future Directions

In examining the challenges, the reviewed studies were categorized into two main groups: those employing traditional methods and computer vision techniques, and those utilizing artificial intelligence (AI) and computer vision for image processing. As illustrated in Figure 6, the analysis of studies based on traditional methods and computer vision indicates that calibration and validation have been identified more frequently than other limitations in this category of research. In other words, to ensure the accuracy of the results, continuous calibration and validation of models and image processing algorithms are necessary, which poses a significant constraint in most studies. Another major limitation in this group is the exclusion of non-visual indicators (e.g., water depth). Since various traditional and computer vision-based image processing techniques rely primarily on visual information analysis, critical factors such as water depth and bathymetry (underwater topography), which significantly influence rip currents, may not be directly detectable. These limitations can directly affect the accuracy of the obtained results.

Another frequently reported challenge is the limitation related to spatial resolution. Although high-resolution images obtained through remote sensing techniques are often available, in some cases, the resolution may still be insufficient for analyzing fine-scale features of rip currents. This issue becomes particularly pronounced in areas with dense vegetation or turbid waters, where detecting and tracking rip currents becomes problematic.

Other reported challenges and limitations, in order of frequency, include the influence of tides and waves, atmospheric conditions, rapid variability of currents, precise boundary delineation of currents, seasonal and annual variations, surface cover effects, and various environmental factors.

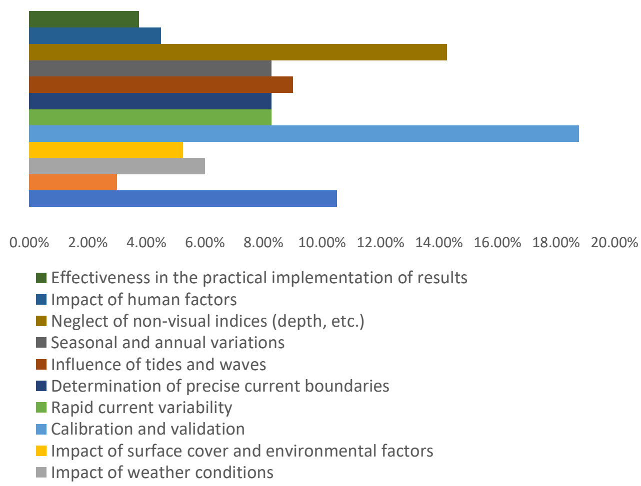

Figure 6. Percentage of challenges in image processing based on traditional methods and computer vision.

Figure 7 presents a comparison of the challenges identified in studies that utilize artificial intelligence (AI) and computer vision for image processing. Among the various limitations, spatial and temporal constraints are among the most frequently reported challenges in this group of studies. In other words, the results obtained in each study often face significant difficulties in terms of model generalization. This is primarily due to the fact that most AI models are trained on specific datasets and may not perform well under different conditions or in other geographical locations.

Challenges related to insufficient and noisy data, limitations in defining different flow classes, uncertainty in input data, and the “black-box” nature of AI models (i.e., the lack of transparency in how results are derived) have been reported with similar frequency across the literature. Other notable challenges, in descending order of occurrence, include the unavailability of trained models for benchmarking, rapid and nonlinear flow variations, high computational costs, and inadequate labeling of the datasets used.

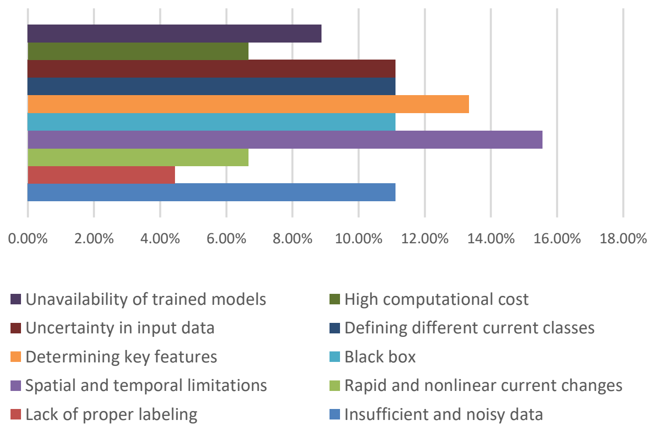

Figure 7. Percentage of challenges in image processing based on artificial intelligence tools and computer vision.

In this study, heatmap analysis of the challenges and limitations in various studies has been employed as a powerful approach to better understand these areas and guide future research. By identifying the challenges and weaknesses of each specific technique, innovative solutions can be proposed to advance remote sensing and artificial intelligence studies, ultimately unlocking the full potential of these technologies.

Figure 8 presents a heatmap of different remote sensing tools (such as Radar, Aerial Imagery, etc.) along the horizontal axis and various challenges and limitations of remote sensing (such as Temporal resolution, Spatial resolution, etc.) along the vertical axis. Each cell in this heatmap indicates the intensity of the relationship between a specific challenge and a particular tool. Warmer colors denote stronger correlations, while cooler colors indicate weaker correlations.

The heatmap in Figure 8 highlights various aspects, including general challenges common to all remote sensing tools, such as seasonal and annual variations and the lack of non-visual indicators (e.g., depth) in the use of different remote sensing tools. These challenges are present in almost all remote sensing tools, with none of them being entirely unaffected (absence of red, or completely cold colors). The primary reason for the commonality of the seasonal and annual variation challenge across all remote sensing tools is the changes in vegetation cover across different seasons, which affect the reflection of light from the Earth's surface and, consequently, the pixels in satellite images. Changes in water resources, such as rainfall, evaporation, and transpiration throughout the year, influence the amount of water on the Earth's surface, soil moisture, and the depth of surface waters, all of which are visible in satellite imagery. Additionally, changes in atmospheric phenomena, in line with seasonal variations, impact the quality of satellite images, complicating their interpretation. The shared challenge of the lack of non-visual indicators in all remote sensing tools is attributed to the limitations of the remote sensing sensors. Most remote sensing sensors are sensitive to visible, near-infrared, and thermal infrared spectra. These sensors provide information on light reflection from the Earth's surface but do not offer details about subsurface features such as depth, temperature, etc. The complexity of natural phenomena, such as rip currents, also contributes to the shared challenge of not accounting for non-visual indicators in all remote sensing tools for rip current detection.

Moreover, Figure 8 significantly aids in identifying the major challenges associated with each remote sensing tool. For instance, due to the widespread use of aerial imagery as the most common remote sensing technique, the challenge of calibration and validation is shown as the most frequently encountered challenge (represented by dark green) in this technique. This challenge is also depicted as the most influential (dark green) in satellite imagery techniques. This indicates that calibration and validation can impact the accuracy of both aerial and satellite imagery techniques. Thus, the strengths and weaknesses of each remote sensing technique in dealing with various challenges can be identified. It is also noteworthy that in both aerial and satellite imagery techniques, the impact of surface cover and environmental factors and impact of weather conditions on the accuracy of the techniques are significant. However, in these two remote sensing techniques, temporal resolution (the time interval between two consecutive images) is not a major challenge. This is because aerial imagery allows for more flexibility in the timing of flight missions, making it much easier to capture aerial images at different times and locations. On the other hand, in rip current studies, parameters such as flow speed, flow direction, wave height, and wave breaking patterns are much more critical and challenging than temporal resolution. These parameters can be extracted using satellite images with appropriate spatial resolution and image processing techniques.

According to Figure 8, spatial resolution (the smallest detail that can be distinguished in an image) is another challenge that is particularly notable in radar imagery from various remote sensing tools. According to the findings from related studies, one of the main reasons for the limitation of achieving very high spatial resolution in radar images is the technical constraints of radar systems. In other words, the spatial resolution of radar systems depends on various factors, such as operating frequency, antenna size, and distance to the target. Given the specific characteristics of rip currents—such as their small size and rapid changes—the spatial resolution limitation in radar imaging is a major challenge in rip current studies. However, this challenge can be partially addressed through the use of various techniques and the development of new technologies.

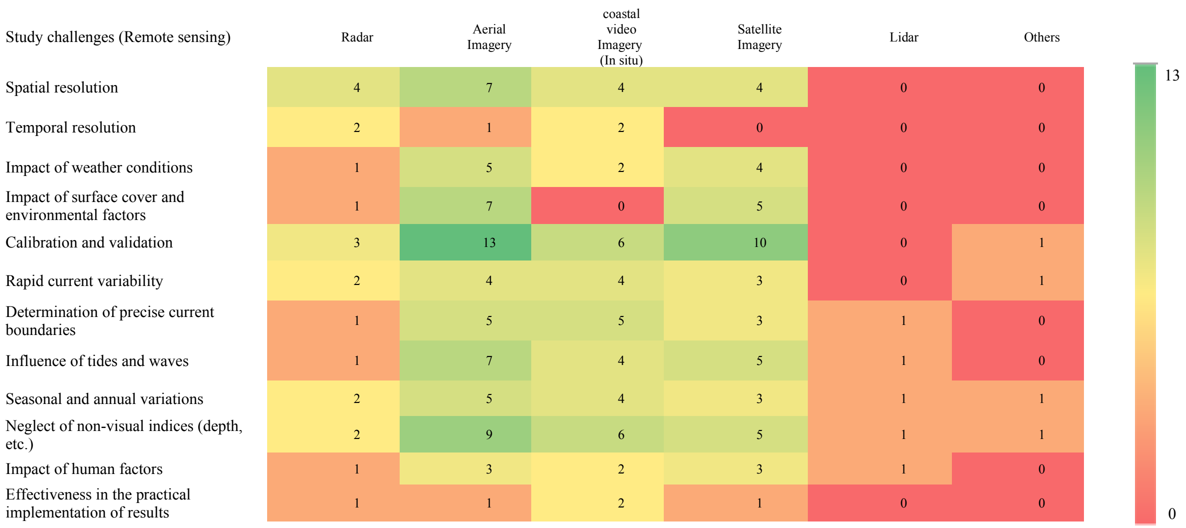

Figure 8. Heat map showing the study challenges against a variety of RS techniques.

Figure 9 presents a heatmap of various techniques and hybrid tools in artificial intelligence (e.g., Machine Learning (SVM), Machine Learning (CNN), Deep Learning (Faster R-CNN), etc.) along the horizontal axis, and various challenges encountered in employing these methods (e.g., Lack of proper labeling, Insufficient and noisy data, Rapid and nonlinear current changes, etc.) along the vertical axis. Each cell in the heatmap indicates the intensity of the relationship between a specific challenge and a particular technique. Warmer colors denote stronger correlations, while cooler colors indicate weaker correlations.

The heatmap in Figure 9 illustrates the challenges encountered with each specific AI technique. The results show that, in machine learning methods such as CNN and SVM, the primary challenges are related to model generalization (spatial and temporal limitations), challenges in interpreting results (black-box nature), and specific challenges in studying rip currents (identifying key features).

In other deep learning techniques and hybrid methods, including LSTM, JDC, Grad-CAM, Faster R-CNN, and Tiny-YOLOv3 & RipDet+, no specific recurring challenge is observed. However, in the two deep learning techniques, Faster R-CNN and Tiny-YOLOv3 & RipDet+, the challenge of insufficient and noisy data, which pertains to the quality of input data, is identified as the most impactful limitation in rip current studies. As noted, both of these techniques are object detection models widely used in the field of computer vision, with Faster R-CNN known for its high accuracy and Tiny-YOLOv3 for its high speed. Consequently, both models require high-quality and large volumes of training data, and insufficient training data may lead to problems such as overfitting or underfitting. Additionally, noise in the data can reduce the model's accuracy. Since RipDet+ is specifically designed for rip current detection, it requires training data with accurate and domain-specific labeling.

On the other hand, aside from the high cost and time involved in collecting and labeling rip current data, the complexity and variable nature of rip currents make it highly challenging to gather diverse and representative data for this phenomenon. All these factors make the challenge of insufficient and noisy data the most prominent limitation in rip current studies for the two aforementioned techniques.

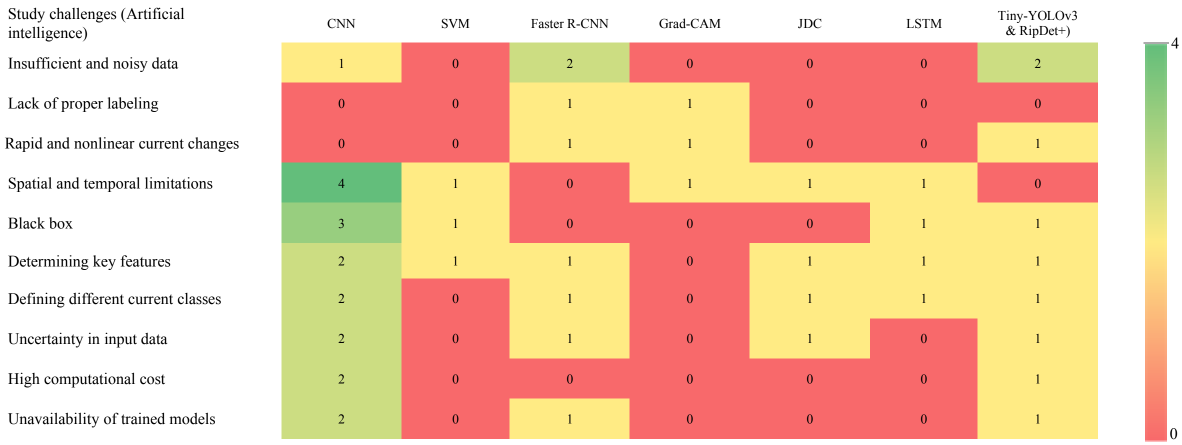

Figure 9. Heat map showing the study challenges against a variety of AI techniques.

5. Conclusions

This study provides a comprehensive review of the application of various image processing and remote sensing techniques in rip current studies. The findings revealed that combined processing methods, particularly those utilizing multi-source data (coastal surveillance cameras, satellite imagery, and drones), were the most widely used (approximately 78% of the studies). Additionally, studies combining classical image processing with machine learning and flow analysis have been more successful in accurately detecting rip currents.

Among remote sensing imaging methods, optical imagery, with a share of 81.39%, has been the most commonly used due to its high resolution, lower cost, and ease of interpretation. It is worth noting that while aerial imagery, with a share of 38.77%, has been one of the most widely used methods in rip current studies due to its higher spatial resolution and flexibility in data collection, satellite imagery, with a share of 24.48%, has also held a significant position. However, the combination of these images with other data, such as radar and sonar, can provide more comprehensive information about coastal environments.

Regarding the use of artificial intelligence tools, Convolutional Neural Networks (CNN), with a share of 33.33%, have been identified as the most widely used method in rip current image processing due to their ability to automatically extract complex visual features and their resilience to noise. Other AI models, such as Faster R-CNN and Tiny-YOLOv3, have also been used for object detection in images, but CNNs are more popular due to their greater flexibility and ability to learn more complex features.

The results indicated that the main focus of studies has been on the detection of rip currents (38%), while tracking (22%) and continuous monitoring (18%) of these currents have received less attention. One of the reasons for this is the technical challenges and high costs associated with establishing and maintaining monitoring systems. Additionally, the rapid changes in rip currents and the need for long-term, high-quality data to assess the effectiveness of monitoring and tracking methods have been other significant barriers.

The review of challenges in the studies revealed that limitations related to model calibration and validation, the failure to consider non-visual indicators (such as depth and underwater topography), inappropriate spatial resolution, and the impact of weather conditions were among the common problems in traditional image processing and computer vision methods. In AI-based studies, challenges related to the generalization of models, insufficient and noisy data, and uncertainty in defining the classes of rip currents were considered major obstacles. Overall, the results of this study indicate that combining image processing, remote sensing, and artificial intelligence techniques can enhance the detection, tracking, and monitoring of rip currents. Furthermore, the development of AI models with high generalization capability and the integration of multi-source data can pave the way for future research in this field.

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