International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. #, No.# (Mon-20..)

Deep Learning Approach for Eddy Detection in Bay of Bengal using SPA -YOLO

Saritha S[1], Preetha K G[2], Jishnu Jeevan[3], Chinnu Sachidanandan[4], Joel Manuel C J[4]

[1,,2,4] Rajagiri School of Engineering & Technology, Kochi, India
[3]Euro-Mediterranean Center on Climate Change (CMCC), Italy
[4]Ignitarium Technology Solutions, Kochi, India

E-mail address: saritha_s@rajagiritech.edu.in,preetha_kg@rajagiritech.edu.in, jishnu.jeevan@cmcc.it, sarunkt@rajagiritech.edu.in, joel.cj@ignitarium.com

Abstract: Eddy detection is crucial for understanding ocean dynamics and their impact on marine ecosystems. This paper introduces a new method based on the You Only Look Once (YOLO) deep learning algorithm for identifying ocean eddies in the Bay of Bengal. The model is trained on satellite-derived Sea Surface Height (SSH) and Sea Surface Temperature (SST) datasets to identify and categorize eddy structures, utilizing YOLO's real-time object detection capabilities. Our approach combines preprocessing stages, such as data normalization and augmentation, to improve the accuracy and resilience of the model. Additionally, we integrate a Spatial Attention (SPA) module into YOLO, creating SPA-YOLO, which enhances the model's ability to focus on relevant spatial features within the data. This integration allows for more precise identification of cyclonic and anticyclonic eddies by emphasizing critical regions in the input data. The trained SPA-YOLO model outperforms other approaches in terms of precision and recall. Experimental results highlight the model's efficiency in processing large-scale oceanographic data, providing timely and accurate eddy detection. This research contributes to the advancement of ocean monitoring systems, offering a scalable and dynamic solution for marine researchers and policymakers. The application of SPA-YOLO in this context underscores the potential of deep learning techniques in enhancing the understanding of complex oceanographic phenomena, thereby supporting efforts in climate research, marine biodiversity conservation, and sustainable ocean resource management.

Keywords: Ocean, Deep Learning, Eddy, YOLO,Bay of Bengal

1. Introduction

Heat, energy, nutrients, and tracers are transported through the ocean circulation system, playing a crucial role in global climate regulation and marine ecosystem health [1]. A significant component of this system is the transfer of kinetic energy via oceanic vortices, known as meso-scale eddies. These compact marine formations vary in radial size and can endure from several days to several months, moving in circular or elongated trajectories. Meso-scale eddies are classified into two types: cyclonic eddies, which have cold cores and rotate anticlockwise in the northern hemisphere (clockwise in the southern hemisphere), and anticyclonic eddies, which have warm cores and rotate clockwise in the northern hemisphere (anticlockwise in the southern hemisphere).The Bay of Bengal (BoB) [2,3], the largest bay globally, is situated in the northeastern region of the Indian Ocean and is noted for its dynamic bathymetry and diverse climatic extremes, ranging from seasonally reversed monsoons to tropical cyclones. The NE monsoon prevails in winter, while the SW monsoon dominates summer in the BoB, leading to alternating cyclonic and anticyclonic circulation in the western part of the bay. The East Indian Coastal Current, a significant western boundary current, reverses its direction twice a year, adding to the complexity of the region's ocean dynamics. Studies reveal that these seasonally reversing currents and the associated dynamics foster numerous mesoscale cyclones in the BoB[4,5].

E-mail:author's email

The strong seasonal changes brought by the monsoon cycle affect ocean currents, leading to the frequent formation and dissipation of eddies. The influx of freshwater from major rivers like the Ganges, Brahmaputra, and Irrawaddy creates strong salinity gradients that contribute to eddy generation. Eddies in the Bay of Bengal are important for understanding the region's heat and salt transport, as they play a crucial role in the lateral movement of these elements, impacting broader climate and weather patterns. Additionally, eddies enhance biological productivity by upwelling nutrients from the deep ocean, supporting marine ecosystems. Studying these phenomena provides insights into the region's marine life and can serve as indicators of climate change impacts on ocean circulation, aiding in better weather forecasting, climate modeling, and marine resource management.

In the era of Artificial Intelligence, deep learning—a subset of AI that mimics the neural networks of the human brain—has revolutionized various domains[6]. Unlike traditional machine learning, deep learning performs tasks without explicit programming, using artificial neural networks composed of layers of neurons that process data. Pre-trained models in deep learning are crucial as they offer a significant head start by leveraging knowledge gained from large, diverse datasets, allowing for faster and more efficient training on specific tasks. They help in achieving better performance even with limited labeled data, as the models have already learned to extract meaningful features. By using pre-trained models, researchers can save considerable computational resources and time that would otherwise be spent on training from scratch. [7].

The proposed work leverages the power of deep learning to detect eddies in the BoB. By utilizing pre-trained deep learning models, neural network architectures pre-built for high performance, to improve the accuracy and efficiency of eddy detection. This approach not only enhances our understanding of oceanic processes in the BoB but also underscores the potential of deep learning techniques in advancing oceanographic research and contributing to climate studies, marine biodiversity conservation, and sustainable ocean resource management. The contributions of the proposed work are as follows.

- To improve the accuracy and efficiency of detecting meso-scale eddies in the Bay of Bengal, by integrating a Spatial Attention module with You Only Look Once (YOLO) model of deep learning algorithm and thus surpass the traditional methods.
- To provide a comprehensive approach to eddy detection that captures both cyclonic and anticyclonic structures, by utilizing sea surface height (SSH) and sea surface temperature (SST) datasets.
- To demonstrate the potential of deep learning techniques in ocean monitoring, contributing to better understanding and management of oceanographic phenomena, climate research, and marine ecosystem conservation.

The paper is outlined as follows. The related work is briefly described in Section 2. Section 3 details about the steps in the design of the proposed methodology using the deep learning model. The results and discussions are provided in Section 4. Section 5 provides a brief conclusion and future research pointers.

2. Related Work

A lightweight eddy detection method called GED-YOLO was presented by the authors of [8]. The authors compared the performance of GED-YOLO and the traditional eddy detections approaches, it is noticed that both have comparable detection performance, but GEDYOLO outperform in terms of detection speed. The proposed approach utilized a spatial pyramid pooling network to enhance features and incorporated the ECA+ GhostNet as the backbone. This study introduced a feature fusion technique for the ghost eddy detection path aggregation network and thus reduced the number of parameters involved.

Authors in [9] present a deep learning approach that leverages attention mechanisms for the recognition of ocean eddies. This method employs attention modules, which are collated with an encoder model based on convolutional blocks. The spatial attention module aggregates features at every location by summing the data across all points. Meanwhile, the channel attention module extracts relevant information to emphasize interdependent channel maps. To further improve feature representation and achieve more accurate segmentation results, the original feature map is combined with the feature map produced by the attention mechanism. The study's results demonstrate a notable improvement in the accuracy of eddy recognition.

Pixel-by-pixel detection of ocean eddies and automatic semantic segmentation are made possible using the deep convolutional neural network model described in the research [10,11]. Pixel-level recognition in semantic segmentation requires effective context understanding. The context knowledge in the data is captured with the support of attention modules, which are self-made in nature. Along with the same, a pyramid component that retains the hierarchical context of the scaled versions of the image and their associated features are also extracted.

This feature enhancement improves the results of the proposed work by the authors.

To find the eddies, the authors of [12] employ a conventional encoder-decoder CNN architecture. Five basic blocks—batch normalisation, convolutional layers, and activation—make up the encoder stage. A max pooling layer that shrinks the image size to better detect eddy characteristics comes after each block. In order to distribute the identified eddy features throughout the altimetry image, an up-sampling layer resizes the image to its original size prior to each block in the decoder stage. The CNN output does not distinguish between cyclonic and anticyclonic activity; instead, it provides a probability value for each pixel that can be used to determine whether or not it is a part of an eddy.

In [13], there are two proposed attention modules. The suggested study illustrates a contextual interaction in the channel and spatial dimensions using a U-Net architecture based on VGG16 and two attention modules. Based on correlations, each pixel or channel adjusts to incorporate the context from every other pixel or channel. In addition, a novel residual channel is suggested as a substitute for the traditional methods to connect the encoder and decoder units. The trial results demonstrate that, in comparison to the current approaches, incorporating a novel residual path and attention-based deep framework increases the model performance.

3. PROPOSED METHODOLOGY

The design of the proposed methodology is given in Figure 1. The process begins with the collection of Sea Level Anomaly (SLA) data, which is used to create an SLA image. Geostrophic current data, comprising u (east-west) and v (north-south) components, is then utilized to generate a u-v vector plot that illustrates the direction and magnitude of ocean currents. These two datasets are combined to form a comprehensive representation of the ocean's dynamic state, integrating the SLA image with the current vector plot.This combined image serves as the input for the YOLO (You Only Look Once) [14,15] deep learning algorithm, renowned for its real-time object detection capabilities. YOLO is used to label the image, identifying and categorizing various ocean features, including eddies. However, to enhance the model's precision and focus, a Spatial Attention (SPA) module is integrated into YOLO, resulting in the SPA-YOLO model. The SPA module improves the model's ability to concentrate on relevant spatial features within the data, highlighting critical regions that are most likely to contain eddies.The SPA-YOLO model is then employed for the detection of cyclonic and anticyclonic eddies in the Bay of Bengal.

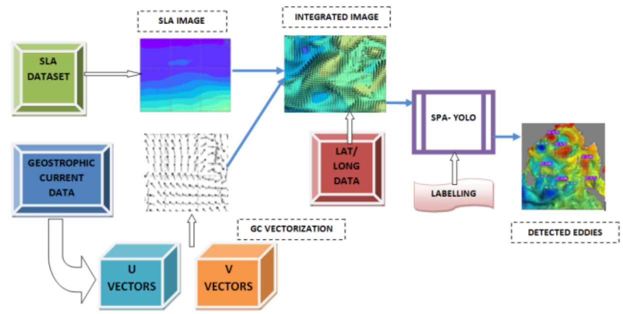

Figure 1. Proposed Methodology

A. Data Set

The period of study chosen for this work is 2015, 2016 and 2019. El Niño/ Southern Oscillation (ENSO) [18, 19] and Indian Ocean Dipole (IOD) [20, 21] are the two inter-annual phenomena that motivated for the selection of the particular years. It is observed that strong ENSO and positive IOD co-occurred in 2015 and 2019, while La Niña and negative IOD co-occurred in 2016.

Copernicus Marine Services (CMEMS) [22] provided daily fields of sea level anomaly, zonal, and meridional components of ocean current velocity that were employed in the current study. From these daily anomalies, respective components are calculated which are used to run the algorithm. The altimetry data package is included in a CMEMS global ocean eddy-resolving (1/12° horizontal resolution, 50 vertical levels) reanalysis called GLORYS12V1[23], is employed in the present study. The NEMO platform, which is powered by ECMWF, ERA (ECMWF Re-Analysis)-Interim and ERA5 reanalysis for recent years [24], is the model component. Furthermore, a 3D-VAR [25] approach that corrects the large-scale biases in salinity and temperature is also incorporated into the dataset. GLORYS12V1 [23] also consists of daily and monthly temperature, salinity, sea level and MLD, which is also used in this study. On a typical regular grid, the worldwide ocean output files are at 1/12° (about 8 km).

B. YOLOv7 Detection Network

YOLO (You Only Look Once) is a series of real-time object detection models. YOLOv1 introduced a single neural network predicting bounding boxes and class probabilities directly from full images. YOLOv2 and YOLOv3 improved accuracy and speed with features like anchor boxes and multi-scale predictions. YOLOv4 and YOLOv5 further enhanced performance using advanced techniques like data augmentation. YOLOv6 and YOLOv7 continue to refine the architecture, achieving higher precision and faster inference with innovations in network design and training strategies.The YOLO architectures from V1 to V7 [16,17] have continuously improved the object detection accuracy and speed.

YOLOv7 differs from its previous version in terms of its model structure. The architects of YOLOv7 have concentrated on optimizing training process and improving accuracy without an overhead in computational parameters and power. The YOLO Detection network is shown in Figure 2. There are four major components in the YOLO model (i) Input (ii) Backbone (iii) Neck and (iv) Head.

The batch of images is inputted into the backbone of the YOLO network. The backbone of YOLO is the major constituent responsible for extracting the features from the input images. The backbone consists of four CBS modules (Convolution + Batch Normalization + Activation (Sigmoid) + Stride -1) which are connected in series, four ELAN modules and three Max Pooling (MP) modules. The CBS modules are the basic building blocks of all components of YOLO like ELAN, MP and SPPCSPC(Spatial Pyramid Pooling Cross Stage Partial). The ELAN module is the key feature extractor in the network which housesseven CBS modules. The first two CBS modules in the ELAN get their input from previous layers and the output from the first CB is fed to the successive four CBS in series. The output from the first and second CBS, and four CBS (in series) is concatenated and is fed to seventh CBS. The MP module is made of a Max Pooling Unit and three CBS modules and is connected after ELANs in the backbone. The Max Pooling Unit and the first CBS module receive input from the seventh CBS module of ELAN. The output of the Max Pooling Unit is fed to second CBS, and the output of the first CBS is fed to the third CBS. The output from the first CBS and third CBS are further concatenated.

The neck component concatenates the feature maps extracted by the backbone and fed into the head, effectively linking the two. The head then generates the final eddy detections using bounding boxes. The ELAN in the backbone is fed into the SPPCSP. The head solves the problem of redundant gradient information by obtaining multiscale area characteristics by max pooling and associated processes. The concatenation of all CBS modules are done in ELAN-W in the head, whereas only four of them are concatenated in the backbone to form ELAN. The MP2 module differs from MP1, in the context that it has an additional input from ELAN-W. The output of ELAN-W blocks is fed to REP layers for final object detection. The final detection tensor contains the bounding boxes for each eddy detected in the input image, the objectness score, and the expected confidence which is a probability of belonging to a particular class.

C. SPA-YOLO (SPatial Attention module integrated YOLO)

This study introduces SPA-YOLO, a novel approach for detecting meso-scale eddies in the Bay of Bengal by integrating a Spatial Attention (SPA) module into the You Only Look Once (YOLO) deep learning algorithm. The SPA-YOLO architecture is given in Figure 3. Traditional methods of eddy detection often struggle with accuracy and efficiency, particularly in complex and dynamic environments like the Bay of Bengal. SPA-YOLO aims to address these challenges by leveraging the strengths of YOLO's real-time object detection capabilities and enhancing them with the SPA module to focus on relevant spatial features in satellite-derived sea surface height (SSH) and sea surface temperature (SST) datasets.YOLO is renowned for its ability to perform fast and accurate object detection. However, in the context of ocean eddy detection, it is essential to capture subtle and complex features within the data. The integration of the SPA module enhances YOLO's performance by allowing the model to focus on specific spatial regions that are critical for identifying eddies. This attention mechanism helps the model to differentiate between cyclonic and anticyclonic eddies, which have distinctive rotational patterns and thermal cores. The SPA module refines the detection process by emphasizing critical regions within the input data, allowing the model to focus on areas that are more likely to contain eddies.The integration of the SPA module into YOLO detection network results in higher precision and recall rates, indicating that the model is more accurate in identifying and classifying eddies.

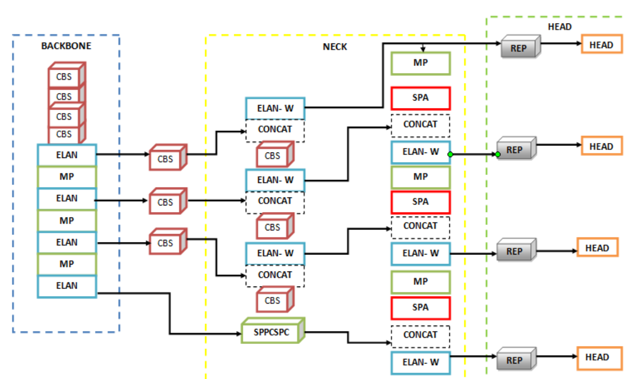

Figure 2. SPA-YOLO Architecture

4. Results and Discussions

The results and analysis of eddy detection using YOLOv7 are illustrated in Figure 2. This figure displays the eddies detected in the Bay of Bengal (BoB), with the detected eddies marked in bounding boxes. These bounding boxes are labeled as CC for cyclonic eddies and AC for anticyclonic eddies, providing a clear distinction between the two types of eddies. The analysis covers the years 2015, 2016, and 2019, chosen as case studies to illustrate how different climatic conditions influence eddy formation and distribution.

Figure 3,4, 5 shows the eddies detected in the years 2015,2016 and 2019 respectively.

In 2015, the detection results reveal a notable pattern of eddy formation, particularly from September to November. This period corresponds with a combination of the Positive Indian Ocean Dipole (PIOD) and El Niño/Southern Oscillation (ENSO) events. During these months, eddies are more prominent around the central Bay of Bengal, suggesting that the combined effects of PIOD and ENSO conditions enhance the formation of eddies. The increased prominence of eddies during this time can be attributed to the altered oceanographic conditions resulting from these climatic phenomena, which influence sea surface temperatures and current patterns, thus fostering the development of eddies. The PIOD, characterized by warmer sea surface temperatures in the western Indian Ocean, and cooler temperatures in the eastern part, creates conducive conditions for eddy formation by altering the thermocline structure and enhancing vertical mixing. Similarly, ENSO, with its widespread impacts on global weather patterns, affects wind stress and ocean circulation, further contributing to eddy dynamics. The interaction between these climatic drivers amplifies the eddy kinetic energy in the region, leading to more frequent and intense eddy events. Additionally, the combined influence of PIOD and ENSO alters the salinity and nutrient distribution, promoting phytoplankton blooms that can be associated with eddy activity. This synergistic effect highlights the complex interplay between large-scale climatic events and mesoscale oceanographic processes in the Bay of Bengal.

In 2016, which was characterized by a pure La Niña year, a similar phenomenon is observed with eddies appearing prominently from September to October, followed by an additional spike in December. La Niña events typically lead to cooler sea surface temperatures and altered current patterns, which may contribute to the observed increase in eddy activity. The detection of eddies in the same months as in 2015 indicates a consistent pattern of eddy formation during the transition periods of the La Niña cycle.For 2019, another PIOD year, eddies are observed to be more prominent from September to October and are clustered around the central to western Bay of Bengal. The clustering of eddies in these regions could be related to the specific oceanographic and climatic conditions prevalent during the PIOD event. The spatial distribution and timing of eddy occurrences provide valuable insights into how PIOD conditions influence ocean dynamics and eddy formation.

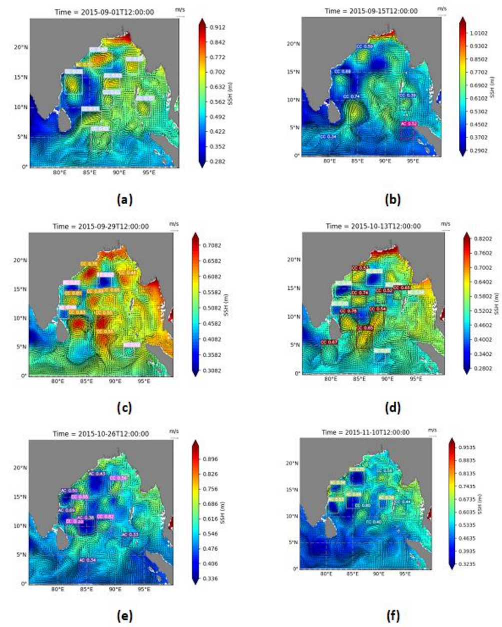

Figure 3. Eddies Detected in 2015

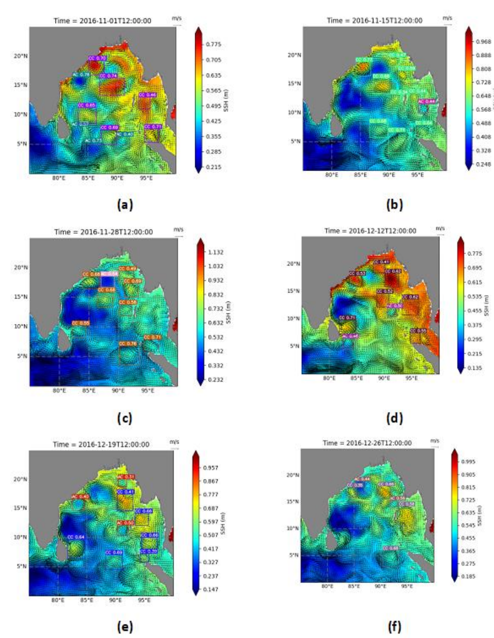

Figure 4. Eddies Detected in 2016

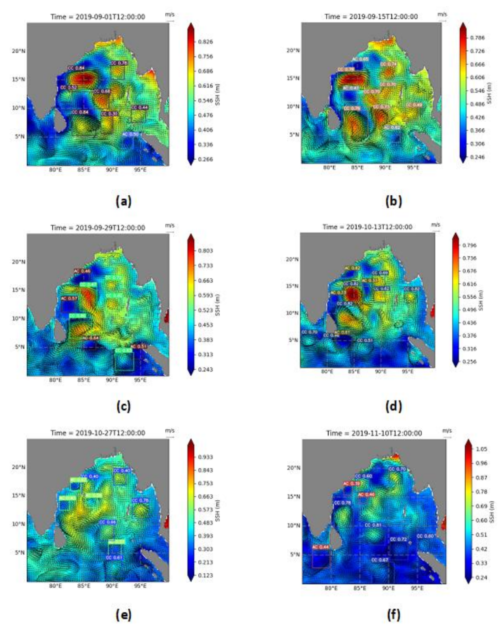

Figure 5. Eddies Detected in 2019

SPA-YOLO is trained for 160 epochs, and various metrics were computed to evaluate the model's performance. It was observed that the recall starts to drop off at 160 iterations. This observation indicates that while the model's performance in identifying eddies improves with more training epochs up to 160, there is a point where further iterations do not yield significant improvements in recall,and may even lead to overfitting. Consequently, training was completed at 100 epochs to balance performance and generalization.

The performance of the proposed classification model is evaluated based on Precision, recall, and F1-score.

The precision vs. recall graph from the SPA-YOLO model for eddy detection depicted in Figure 6 indicates the performance of the model in identifying cyclonic and anticyclonic eddies. It is observed that both cyclonic and anticyclonic eddies have a value of 0.709, suggesting that the model performs equally for both types of eddies. A precision of 0.709 means that 70.9% of the detected eddies are correctly identified (true positives), and the rest are false positives. Recall, also 0.709, indicates that 70.9% of the actual eddies are correctly detected by the model, while the remaining 29.1% are missed (false negatives). This balanced precision and recall imply that the model has a good trade-off between identifying most of the true eddies and maintaining a low number of false positives. However, the identical values for both eddy types suggest that the model doesn't favor one type over the other, providing a uniform performance. The increase in false positives is also seen in the graph, where a drop in precision with increasing recall is observed.

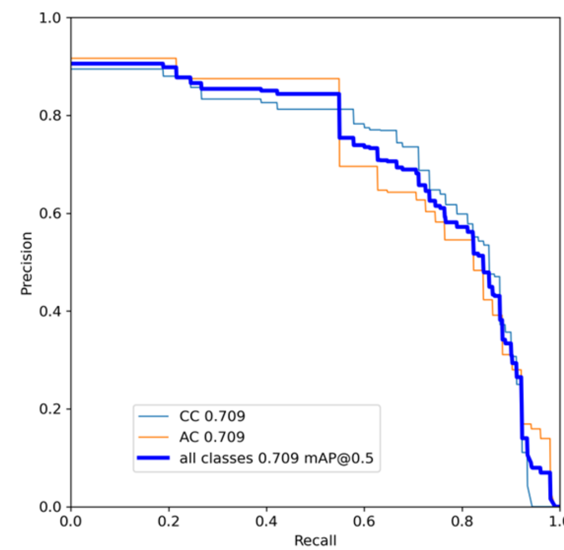

Figure 6. Precision Vs Recall

Yet another metric of evaluation is "Confidence". Confidence refers to the SPA – YOLO model's certainty about the presence of an object and its classification. It is a probability score ranging from 0 to 1, indicating how confident the model is that a particular detected region contains an object of interest. Figure 7 (a-c) depicts the confidence analysis with respect to precision, F1-score and recall. Figure 7(a) shows how the precision of the model changes with different confidence thresholds. As the confidence threshold increases, it is seen that the model becomes more conservative, only making predictionswhen it is more certain. The precision increases with higher confidence thresholds because the model reduces false positives, though it may also miss more true positives. However, there is a dip observed in precision after the confidence score reaches 0.8. Figure 7(b) illustrates how the recall changes with different confidence thresholds. It is observed from the graph that as the confidence threshold increases, recall typically decreases because the SPA-YOLO model has become more selective and misses more true positives. However, at lower confidence thresholds, the model captures more true positives, but it may also increase the number of false positives, thus lowering precision. Figure 7 (c) shows how the F1 score changes with different confidence thresholds. The F1 score is useful for finding the optimal confidence threshold that balances precision and recall. A peak in the F1 score indicates the best trade-off between precision and recall, indicating an optimal threshold of 0.7 for eddy detection.

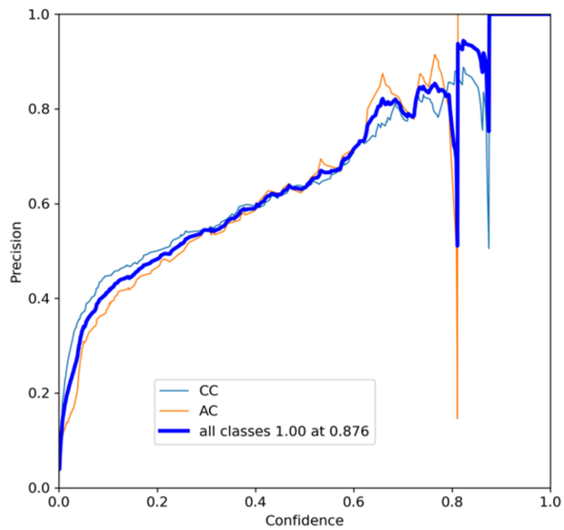

Figure 7. (a) Confidence Vs Precision

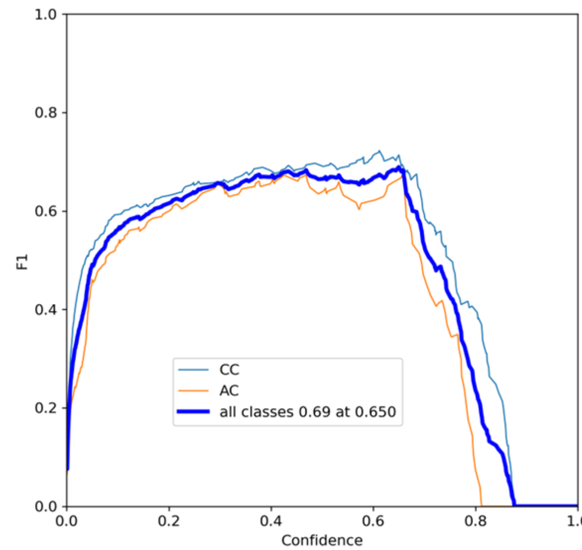

Figure 7. (c) Confidence Vs F1 – score

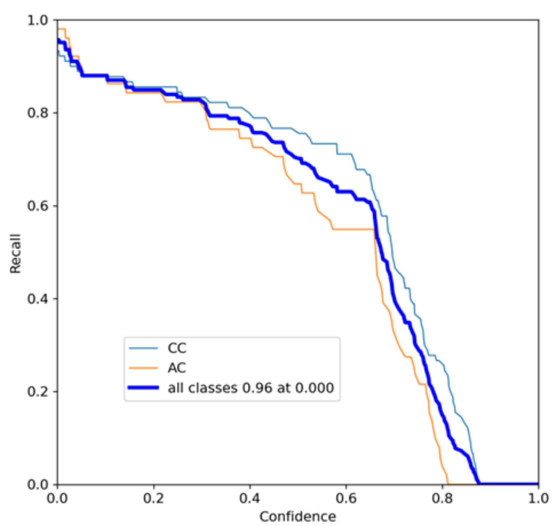

Figure 7(b) Confidence Vs Recall

To assess the efficacy of SPA-YOLO, a comparative evaluation was conducted using traditional eddy detection methods, including the Okubo-Weiss (OW) criterion and the winding angle approach. These traditional methods are based on mathematical formulations that analyze the vorticity and deformation fields in oceanographic data to identify eddies.

- **Okubo-Weiss Criterion:** The Okubo-Weiss (OW) criterion is a well-established method for identifying coherent vortices by examining the balance between vorticity and strain in the ocean. While this method provides valuable insights into the presence of eddies, it often requires careful tuning of parameters to achieve accurate results. Additionally, the OW criterion may struggle with detecting smaller or less defined eddies, leading to potential underestimation of their presence. Despite its limitations, the OW criterion remains a widely used tool in oceanography for its ability to highlight larger and more prominent eddies, contributing significantly to our understanding of oceanic vortex dynamics.
- **Winding Angle Method:** The winding angle (WA) method focuses on analyzing the rotational characteristics of flow fields, providing an effective means of detecting rotational structures such as eddies. By examining the angular changes in the flow, the WA method can identify regions of coherent rotation, highlighting the presence of vortices. However, this method may

face limitations when distinguishing between closely spaced or overlapping eddies.

Table 1 gives the details of eddies detected for the year 2019 by using different methods.

Table 1: Comparative Analysis of Eddies Detected for the Period August-December 2019

<table>
<tr><th>Method</th><th>AntiCyclonic Eddies</th><th>False Positives</th><th>Cyclonic Eddies</th><th>False Positives</th><th>Actual Anti-Cyclonic Eddies</th><th>Actual Cyclonic Eddies</th></tr>
<tr><td>OW</td><td>38</td><td>19</td><td>42</td><td>12</td><td rowspan="3">19</td><td rowspan="3">30</td></tr>
<tr><td>WA</td><td>32</td><td>13</td><td>46</td><td>16</td></tr>
<tr><td>SPA-YOLO</td><td>28</td><td>9</td><td>39</td><td>9</td></tr>
</table>

In the comparative analysis, SPA-YOLO demonstrated superior performance in detecting eddies compared to the OW and winding angle methods. SPA-YOLO's real-time object detection capabilities allow for more detailed identification of eddies, capturing complex patterns and variations more effectively. However, it is important to note that SPA-YOLO is not without its limitations. The model does exhibit some false positives, where non-eddy features are incorrectly identified as eddies. This issue can be attributed to the model's sensitivity to various spatial patterns and its reliance on the training data's quality and diversity.

In summary, the results highlight the effectiveness of SPA-YOLO in detecting eddies in the Bay of Bengal, with variations in eddy detection linked to different climatic conditions. The analysis underscores the importance of considering climatic influences on oceanographic features and demonstrates the potential of deep learning models in advancing our understanding of complex marine phenomena.

5. Conclusions

This study successfully demonstrates the application of SPA-YOLO, enhanced with a Spatial Attention (SPA) module, for detecting ocean eddies in the Bay of Bengal. SPA-YOLO's real-time object detection capabilities, combined with the SPA module, significantly improve the accuracy and efficiency of eddy detection compared to traditional methods such as the Okubo-Weiss criterion and winding angle approach. The model effectively identifies and categorizes cyclonic and anticyclonic eddies, revealing patterns influenced by different climatic conditions, including PIOD and La Niña events. Despite its advantages, SPA-YOLO does exhibit some false positives, indicating areas for further refinement. Future research will focus on addressing the issue of false positives by enhancing the model's robustness and generalization. This may involve expanding the training dataset, incorporating additional oceanographic features, and fine-tuning model parameters. Additionally, exploring advanced deep learning architectures and integrating multi-modal data sources, such as altimetry and in-situ measurements, could further improve detection accuracy. Implementing real-time monitoring systems using SPA-YOLO could also enhance oceanographic research and operational applications, providing timely insights into dynamic marine environments and supporting climate research and marine conservation efforts.

Subsequent investigations into SPA-YOLO will endeavour to tackle the problem of false positives by augmenting the model's resilience and scope. By adding more oceanographic features and growing the training dataset, this can be accomplished. To increase accuracy, adjusting the model's parameters will also be a major priority. To further improve detection capabilities, more research into sophisticated deep learning architectures and the integration of multi-modal data sources including altimetry and in-situ measurements are needed. Operational applications and oceanographic research can be greatly advanced by using real-time monitoring systems that leverage SPA-YOLO. These developments will enhance efforts to conserve the marine environment and study climate change by offering timely insights into dynamic marine habitats.

References

[1] **Duo**, Zijun, Wenke Wang, and Huizan Wang. "Oceanic mesoscale eddy detection method based on deep learning." *Remote Sensing* 11, no. 16 (2019): 1921.

[2] Legeckis, Richard. "Satellite observations of a western boundary current in the Bay of Bengal." *Journal of Geophysical Research: Oceans* 92, no. C12 (1987): 12974-12978.

[3] Babu, M. T., Prasanna S. Kumar, and D. P. Rao. "A subsurface cyclonic eddy in the Bay of Bengal." *Journal of Marine Research* 49, no. 3 (1991): 403-410.

[4] Sharma, Rashmi, A. K. S. Gopalan, and M. M. Ali. "Interannual variation of eddy kinetic energy from TOPEX altimeter observations." *Marine geodesy* 22, no. 4 (1999): 239-248.

[5] Chen, Gengxin, Jianping Gan, Qiang Xie, Xiaoqing Chu, Dongxiao Wang, and Yijun Hou. "Eddy heat and salt transports in

the South China Sea and their seasonal modulations." *Journal of Geophysical Research: Oceans* 117, no. C5 (2012).

[6] Cui, Wei, Jungang Yang, and Yi Ma. "A statistical analysis of mesoscale eddies in the Bay of Bengal from 22–year altimetry data." *Acta OceanologicaSinica* 35 (2016): 16-27.

[7] Hao, Xing, Guigang Zhang, and Shang Ma. "Deep learning." International Journal of Semantic Computing 10, no. 03 (2016): 417-439.

[8] Sun, Haochen, Hongping Li, Ming Xu, Fan Yang, Qiang Zhao, and Cuishu Li. "A lightweight deep learning model for ocean eddy detection." *Frontiers in Marine Science* 10 (2023): 1266452.

[9] Saida, Shaik John, and Samit Ari. "Automatic detection of ocean eddy based on deep learning technique with attention mechanism." In *2022 National Conference on Communications (NCC)*, pp. 302-307. IEEE, 2022.

[10] Saida, Shaik John, Suraj Prakash Sahoo, and Samit Ari. "Deep convolution neural network based semantic segmentation for ocean eddy detection." *Expert Systems with Applications* 219 (2023): 119646.

[11] Santana, Oliverio J., Daniel Hernández-Sosa, and Ryan N. Smith. "Oceanic mesoscale eddy detection and convolutional neural network complexity." *International Journal of Applied Earth Observation and Geoinformation* 113 (2022): 102973.

[12] Franz, Katharina, Ribana Roscher, Andres Milioto, Susanne Wenzel, and Jürgen Kusche. "Ocean eddy identification and tracking using neural networks." In *Igarss 2018-2018 IEEE international geoscience and remote sensing symposium*, pp. 6887-6890. IEEE, 2018.

[13] Saida, Shaik John, and Samit Ari. "MU-net: modified U-net architecture for automatic ocean Eddy detection." *IEEE Geoscience and Remote Sensing Letters* 19 (2022): 1-5.

[14] Wang, Xinning, Xuegong Wang, Chong Li, Yuben Zhao, and Peng Ren. "Data-attention-YOLO (DAY): A comprehensive framework for mesoscale eddy identification." *Pattern Recognition* 131 (2022): 108870.

[15] Mostafa, Seraj Al Mahmud, Jinbo Wang, Benjamin Holt, and Jianwu Wang. "YOLO based Ocean Eddy Localization with AWS SageMaker." *arXiv preprint arXiv:2404.06744* (2024).

[16] Wang, Chien-Yao, Alexey Bochkovskiy, and Hong-Yuan Mark Liao. "YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 7464-7475. 2023.

[17] Alhussainan, Norah Fahd, Belgacem Ben Youssef, and Mohamed Maher Ben Ismail. "A deep learning approach for brain tumor firmness detection based on five different YOLO versions: YOLOv3–YOLOv7." *Computation* 12, no. 3 (2024): 44.

[18] Enfield, David B. "El Niño, past and present." *Reviews of geophysics* 27, no. 1 (1989): 159-187.

[19] Mukherjee, Sayantika, Jayanti Pal, Shaheen Manna, Amrita Saha, and Dipanwita Das. "El-Niño Southern Oscillation and its effects." In *Visualization Techniques for Climate Change with Machine Learning and Artificial Intelligence*, pp. 207-228. Elsevier, 2023. https://doi.org/10.1016/B978-0-323-99714-0.00013-3

[20] Saji, N. H., and T. J. C. R. Yamagata. "Possible impacts of Indian Ocean dipole mode events on global climate." *Climate research* 25, no. 2 (2003): 151-169.

[21] Wu, Jia, Hanjie Fan, Shuheng Lin, Wenxiu Zhong, Shan He, Noel Keenlyside, and Song Yang. "Boosting effect of strong western pole of the Indian Ocean Dipole on the decay of El Niño events." *npj Climate and Atmospheric Science* 7, no. 1 (2024): 6. https://doi.org/10.1038/s41612-023-00554-5

[22] https://data.marine.copernicus.eu/products Access Date - May 15, 2024.

[23] https://data.marine.copernicus.eu/product/GLOBAL_MULTIYEAR_PHY_001_030/description Access Date - May 15, 2024.

[24] https://www.ecmwf.int/en/research/modelling-and-prediction/marine Access Date - May 15, 2024.

[25] Li, Hong, Yi Yang, Jian Sun, Yuan Jiang, Ruhui Gan, and Qian Xie. "A 3D-Var Assimilation Scheme for Vertical Velocity with the CMA-MESO v5. 0." *Geoscientific Model Development Discussions* 2023 (2023): 1-19. https://doi.org/10.5194/gmd-2023-180

Dr Saritha S received the Ph D Degree in Computer Science and Engineering from Cochin University of Science and Engineering, Kerala, India. She is currently serving as a Professor at Rajagiri School of Engineering & Technology (Autonomous) in Kerala, India. She has also contributed numerous journal articles, conference papers, book chapters, and patents.

Dr Preetha K G completed her PhD in Mobile Ad hoc Networks from Cochin University of Science and Technology in 2018. She is currently working as Professor in the Department of Computer Science & Engineering at Rajagiri School of Engineering & Technology in Kerala, India. She has around 22 years of academic experience and contributed numerous publications,

patents and book chapters.

Mr Jishnu Jeevancompleted his B. Tech in Computer Science and Engineering from The Albertian Institute of Science and Technology, Kerala, India in 2018. He completed his M.Tech in Computer and Information Science from The Department of Computer Science, CUSAT, in 2021. Currently he is working as Junior Research Associate, Euro-Mediterranean Center on Climate Change (CMCC), Italy.

Dr Chinnu Sachidanandanis an oceanographer and marine scientist from India. She has completed her graduate studies in oceanography from Cochin University of Science and Technology (CUSAT) and went on to pursue doctoral research in marine sciences at the prestigious CSIR-National Institute of Oceanography.She is currently working as a research fellow in Rajagiri School of Engineering & Technology, in Kerala, India

.

Mr Joel Manuel C J completed his B Tech degree in the year 2024. He is currently working as Associate software engineer in IgnitariumTechnology Solutions, Kochi, Kerala, India