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Implementation of YOLOV5 for Real-time Detection of Ships and Buoys using Jetson Nano and Deepstream on Autonomous Leisure Vessel

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Abstract
System detection on autonomous vehicle have become an increasingly important subject of research in recent years due to their potential to enhance safety and operational efficiency in the maritime sector. This research focuses on the implementation of YOLOv5 for real-time object detection, specifically foreign vessels and buoys, using Jetson Nano and Deepstream. The developed system utilizes serial communication between Jetson Nano and Arduino Mega 2560 to receive and display object detection data. Testing results show that the object detection system achieves 96.66% accuracy during the day and 90% at night. During the YOLOv5 model training, precision of 91.96%, recall of 77.69%, mAP_0.5 of 81.55%, and mAP 0.5:0.95 of 66.23% were obtained. This implementation enables autonomous vessels to detect and avoid objects in real-time, thereby improving safety and operational efficiency at sea
Keywords: *YOLOv5, object detection, maritime safety, real-time detection, autonomous vessel*

Abstrak
Sistem deteksi pada kendaraan otonom telah menjadi subjek penelitian yang semakin penting dalam beberapa tahun terakhir karena potensinya untuk meningkatkan keselamatan dan efisiensi operasional di sektor maritim. Penelitian ini berfokus pada implementasi YOLOv5 untuk deteksi objek real-time, khususnya kapal asing dan buoy, menggunakan Jetson Nano dan Deepstream. Sistem yang dikembangkan menggunakan metode komunikasi serial antara Jetson Nano dan Deepstream untuk menerima dan menampilkan data deteksi objek. Hasil pengujian menunjukkan bahwa sistem deteksi objek memiliki akurasi 96.66% pada siang hari dan 90% pada malam hari. Dalam pengujian training model YOLOv5, diperoleh nilai precision sebesar 91.96%, recall 77.69%, mAP_0.5 81.55%, dan mAP 0.5:0.95 66.23%. Implementasi ini memungkinkan kapal otonom untuk mendeteksi dan menghindari objek secara real-time, sehingga meningkatkan keselamatan dan efisiensi operasional di laut.
Kata Kunci: *YOLOv5, deteksi objek, keselamatan maritim, deteksi real-time, kapal otonom*

1. Introduction

The maritime industry has witnessed significant technological advancements in recent years, particularly in the development of autonomous vessels[1]. Autonomous leisure vessels, equipped with sophisticated navigation and detection systems, have emerged as a promising solution to enhance safety and operational efficiency on the water. One of the critical components of these autonomous systems is real-time object detection, which is essential for the safe operation of vessels in dynamic marine environments[2].

YOLOv5 (You Only Look Once version 5) has emerged as a state-of-the-art algorithm in the field of object detection. Known for its real-time performance and high accuracy, YOLOv5 uses deep convolutional neural networks to classify and localize objects within images. Its capability to process images in real-time makes it particularly suitable for applications in autonomous vehicles, where timely and precise object detection is critical[3].

The NVIDIA Jetson Nano is a compact and powerful edge computing platform designed for running artificial intelligence (AI) applications at the edge[4]. With its 128-core Maxwell GPU, a quad-core ARM Cortex-A57 CPU, and 4 GB of LPDDR4 memory, the Jetson Nano offers substantial computational power in a small, energy-efficient form factor[5]. This makes it particularly well-suited for applications requiring real-time processing of large amounts of data, such as computer vision and machine learning tasks in autonomous systems[6]. The Jetson Nano's ability to perform high-performance AI computations allows it

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to process video feeds and execute complex algorithms like YOLOv5 with minimal latency, which is essential for real-time object detection on autonomous vessels[7]. along with DeepStream is NVIDIA's end-to-end video analytics framework designed to build and deploy real-time, high-performance video processing application[8]s. It provides tools and libraries for efficient video streaming, processing, and analysis, making it an ideal choice for integrating with edge computing platforms like the Jetson Nano[9]. DeepStream supports the deployment of deep learning models, including those based on YOLOv5, and facilitates the development of applications that require high-throughput and low-latency video processing[10]. By leveraging GPU acceleration, DeepStream enhances the performance of object detection models, enabling them to analyze video streams and detect objects with high accuracy and speed [11]. By integrating YOLOv5 with Jetson Nano and DeepStream, autonomous leisure vessels can achieve efficient and accurate real timedetection of ships and buoys, enhancing their ability to navigate and operate safely[12].

This research focuses on the implementation of YOLOv5 for real-time detection of ships and buoys using Jetson Nano and DeepStream on an autonomous leisure vessel[13]. The study aims to evaluate the effectiveness of this integration in improving object detection capabilities and operational safety[14]. By leveraging advanced technologies, this work seeks to contribute to the advancement of autonomous maritime systems and provide insights into their practical applications[15].

2. Material and Methods

A. Data Collection

Data collection is a crucial stage in this research to ensure that the YOLOv5 model can be trained with representative and relevant data for detecting foreign vessels and buoys..

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(a) Before annotation of Ship

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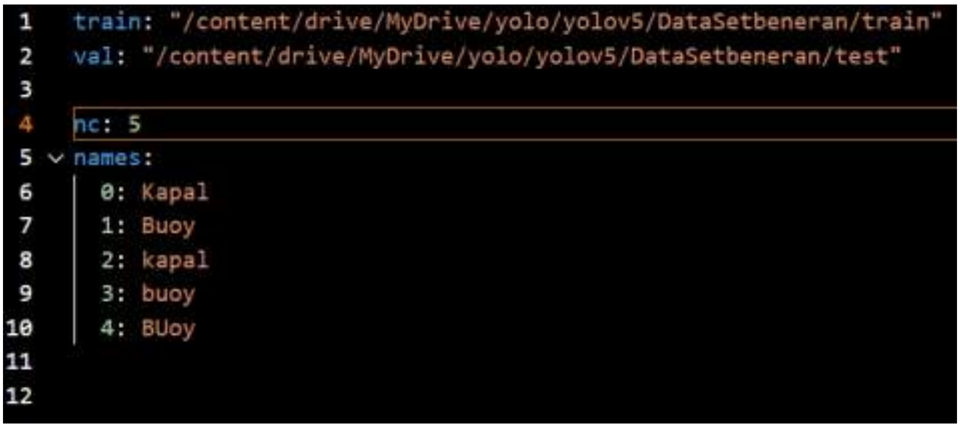
(b) After annotation of Ship


(c) Before annotation of Buoy

(d) After annotation of Buoy

Figure 1. (a),(b),(c),(d) Annotation Ship and Buoy

Figure 1 illustrates the crucial data collection phase in this research to ensure that the YOLOv5 model can be trained with representative and relevant data for detecting foreign vessels and buoys at sea. Figure 1 shows an example of vessel image data collected from real-world environments and the results of annotating these images by placing bounding boxes around the vessel objects. This manual data annotation process is necessary as input for training the object detection model to accurately recognize and detect vessels. Data collection and image annotation are critical steps to ensure optimal detection accuracy of foreign vessels in water surveillance applications



```
train: "/content/drive/MyDrive/yolo/yolov5/DataSetbeneran/train"
val: "/content/drive/MyDrive/yolo/yolov5/DataSetbeneran/test"

nc: 5
names:
  0: Kapal
  1: Buoy
  2: kapal
  3: buoy
  4: BUoy
```

Figure 2. Dataset

Figure 2 above shows the dataset that will be trained by the model, consisting of 1000 ship datasets and 1000 buoy datasets. We encountered a minor error while labeling the data using LabelImg during the annotation process. As shown in the figure, the labeling errors, such as the difference between "Kapal" and "kapal," indicate slight inconsistencies. However, both labels refer to ship datasets.

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B. Connected Jetson Nano remotely using RealVncViewer

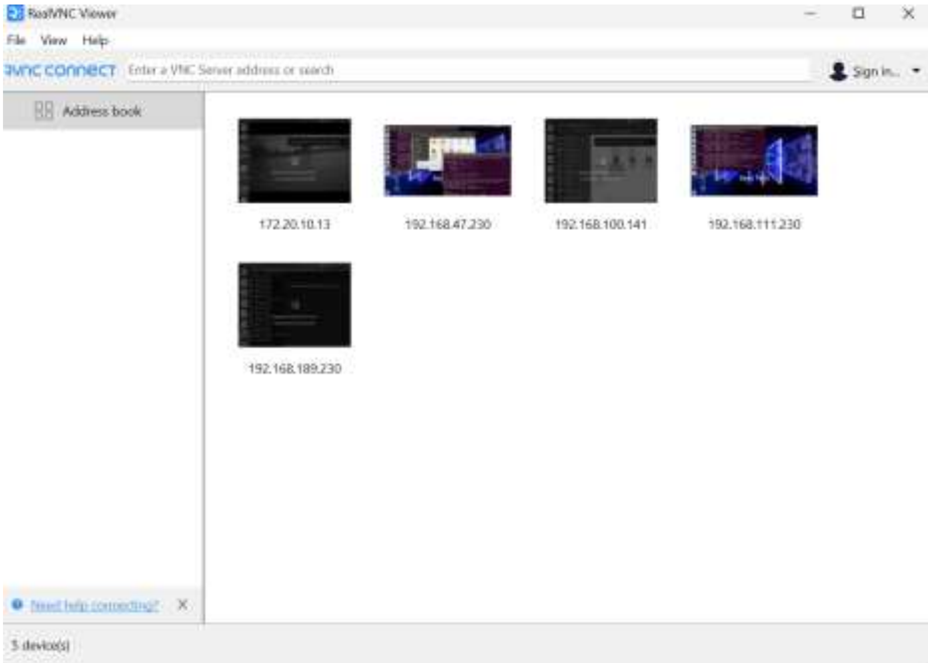

Figure 3. RealVNCViewer

Figure 3 explains the process of connecting to the Jetson Nano via VNC from a laptop. This is done by using the same IP address that connects both the Jetson Nano and the Virtual Network Computing (VNC) client.

C. System Design

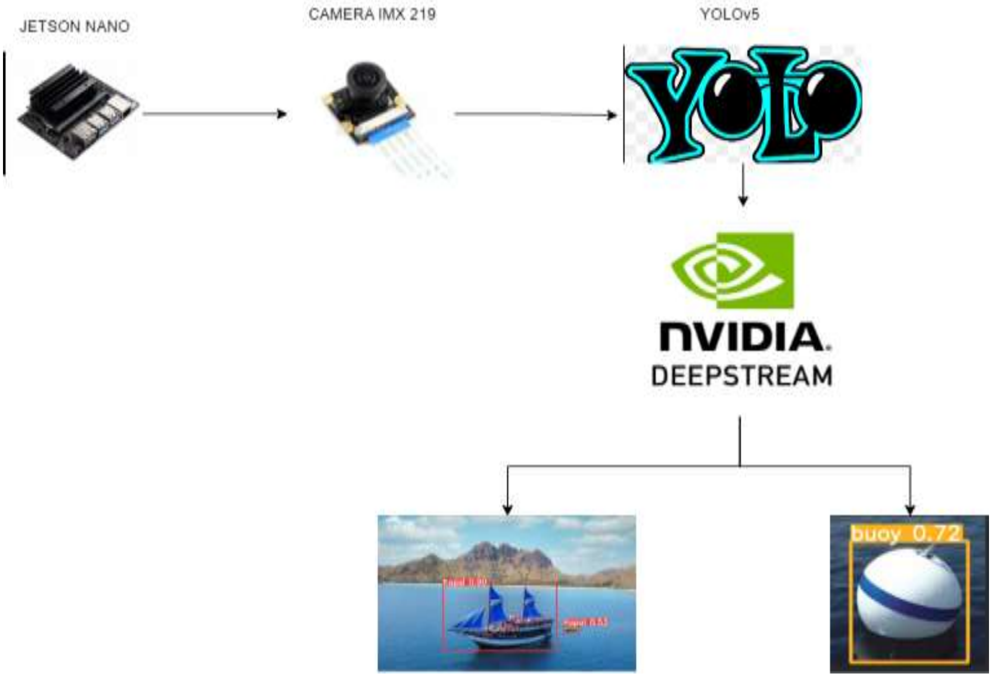

Figure 4. Schematic System on Detection Object

Figure 4 illustrates the Jetson Nano connected to the IMX219 camera to start image or video capture with the IMX219 camera as the input. Subsequently, the YOLOv5 model is applied to perform object detection, and real-time streaming detection features are enabled using DeepStream.

3. Results and Discussion

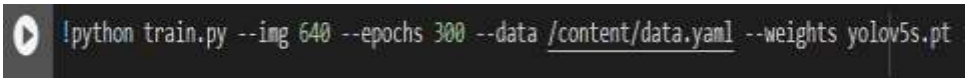

Figure 5. Training of YOLOv5

Figure 5 shows the training process using the YOLOv5 model, which is trained on the prepared dataset. The img 640 indicates that the input images have a resolution of 640x640 pixels. The number of epochs is set to 300 to ensure the model learns effectively from the available data, consisting of 1000 ship datasets and 1000 buoy datasets.

Table 1. Process Training per epoch of YOLOv5

Epoch	Box_loss	Obj_Loss	Cls_Loss	Precision	Recall	mAP_0.5	mAP 0.5:0.95
0	0.0959	0.0402	0.0461	0.3566	0.2258	0.1165	0.0425
1	0.0678	0.0348	0.0313	0.3587	0.3238	0.1711	0.0672
2	0.0644	0.0329	0.0281	0.4112	0.3776	0.1947	0.070
3	0.058	0.032	0.0270	0.4474	0.3755	0.2778	0.1069
4	0.055	0.034	0.024	0.5030	0.3501	0.3058	0.1243
5	0.053	0.034	0.023	0.6133	0.3627	0.3806	0.1496
6	0.052	0.033	0.023	0.5909	0.3856	0.3859	0.1715
7	0.051	0.034	0.021	0.6086	0.4048	0.4010	0.1765
8	0.051	0.033	0.021	0.6011	0.3995	0.3858	0.1710
9	0.050	0.032	0.020	0.6289	0.4039	0.4129	0.1733
……. .	………..	…………	……… …	……… …	……… ….	………..	……… …
291	0.025	0.017	0.0017	0.9221	0.7726	0.8163	0.6610
292	0.0252	0.0183	0.0016	0.92118	0.7729	0.8163	0.6613
293	0.0257	0.0177	0.0017	0.92387	0.7748	0.8159	0.6624
294	0.0253	0.0179	0.0020	0.92338	0.7755	0.8161	0.6622
295	0.0253	0.0172	0.0022	0.92453	0.7749	0.8156	0.6614
296	0.0253	0.0172	0.0018	0.92092	0.7762	0.8154	0.6632
297	0.0252	0.0176	0.0018	0.92176	0.7759	0.8158	0.6621
298	0.0249	0.0180	0.0020	0.92061	0.7760	0.8153	0.6617
299	0.0253	0.0171	0.0020	0.91965	0.7769	0.8155	0.6623

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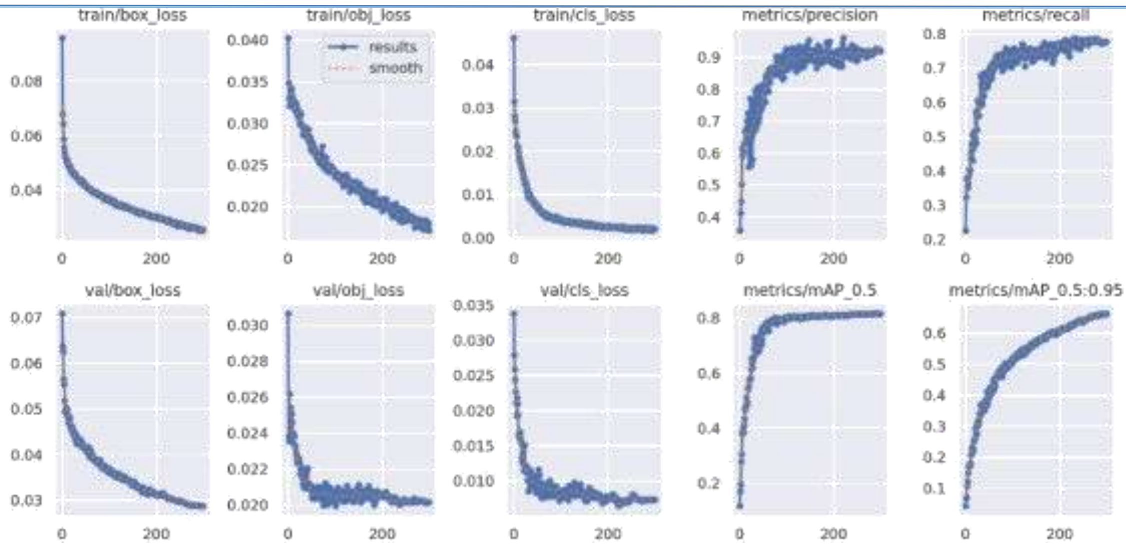
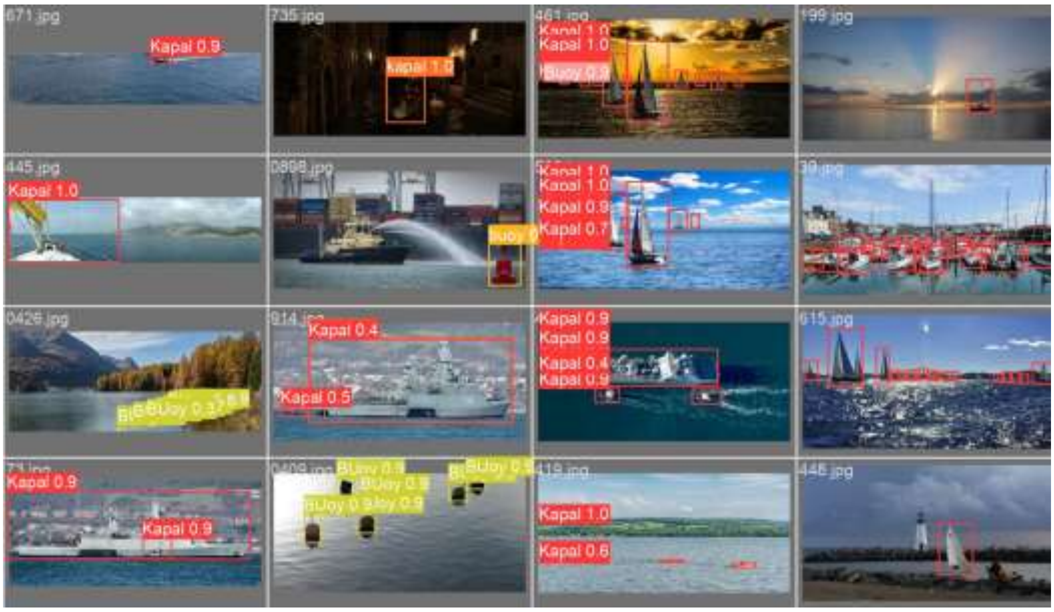


Figure 6. Graphic Results training of YOLOv5

Table 1 and **Figure 6** explained about various performance metrics for the YOLOv5 object detection model during the training and validation process. The graph illustrates the progression of different types of loss and evaluation metrics as the number of epochs increases. It shows the results of training the YOLOv5 model over 300 epochs. In the early epochs, such as epoch 0, the Box_loss, Obj_Loss, and Cls_Loss values were 0.0959, 0.0402, and 0.0461, respectively. Precision and Recall were initially quite low, with values of 0.3566 and 0.2258, while mAP_0.5 and mAP_0.5:0.95 were 0.1165 and 0.0425, respectively. As the epochs progressed, these values steadily improved, indicating that the model was becoming better at adjusting its parameters.

By the final epoch, epoch 299, the Box_loss had decreased to 0.0253, Obj_Loss to 0.0171, and Cls_Loss to 0.0020. Precision had increased to 0.91965, Recall to 0.7769, and mAP_0.5 and mAP_0.5:0.95 had reached 0.8155 and 0.6623, respectively.



(a)

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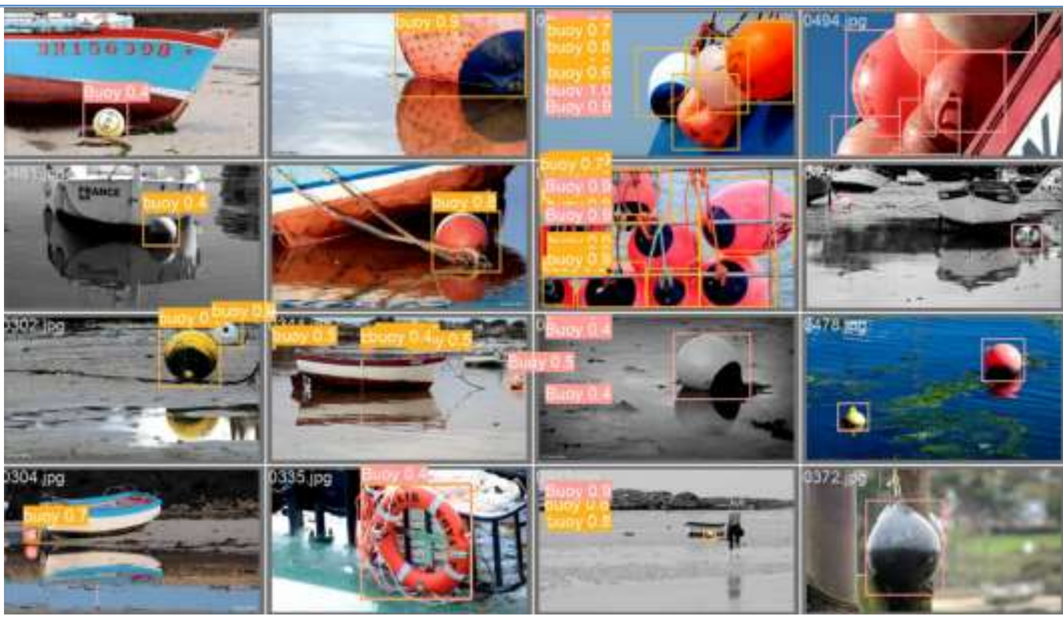

(b)

Figure 7. (a) Results training of Ship, (b) Results training of Buoy

Figure 7 (a), (b) illustrates the training results for sample images of ship objects using the YOLOv5 model. The model, which achieved a Box_loss of 0.0253, Obj_Loss of 0.0171, and Cls_Loss of 0.0020, demonstrates high performance. Precision reached 0.91965, Recall increased to 0.7769, and the metrics mAP_0.5 and mAP_0.5:0.95 achieved 0.8155 and 0.6623, respectively.

```
mirai@mirai-desktop:~/Music/123/Deepstream 5.0$ sudo deepstrea
m-app -c yolo.txt
```

Figure 8. Implementation using Deepstream on Jetson Nano

Figure 8 shows the implementation code for running DeepStream, which is used for real-time streaming detection

(a) (b)

Figure 9. Implementation Detection in Real using Deepstream

Table 2. Trial detection on condition with Luxmeter

Trial	Luxmeter	Detected
1	25632	Yes
2	33521	Yes
3	27425	Yes
4	36713	Yes
5	29526	No
6	42104	Yes
7	24747	Yes
8	35483	Yes
9	37427	Yes
10	41742	Yes
11	36383	Yes
12	23714	Yes
13	42643	Yes
14	15357	Yes
15	36421	Yes

Figure 9 and **Table 2** presents the testing results by implementing real-time object detection using the Jetson Nano and Deepstream. The system is set up to capture video streaming using the DeepStream feature of the camera and perform object detection using the YOLOv5 model. In the experiments shown in the table, 15 trials were conducted, resulting in 14 successful detections with an accuracy of 93.33%.

$$\text{Accuracy} = \frac{\text{Number of correctly detected images}}{Total\ number\ of\ trial\ data}\ x\ 100\% \qquad (1)$$

$$\text{Accuracy} = \frac{14}{15}\ x\ 100\% = 93{,}33\%$$

4. Conclusion

The implementation of YOLOv5 for real-time detection of ships and buoys using Jetson Nano and DeepStream on an autonomous leisure vessel achieved performance metrics of 91.96% precision, 77.69% recall, 81.55% mAP_0.5, and 66.23% mAP_0.5:0.95, as shown in the YOLOv5 graph. The system demonstrated the ability to detect objects around the vessel. Furthermore, under real-world bright conditions, the vessel was able to achieve a detection accuracy of 93.33% from 15 trials. Thus, it is anticipated that this technology will help reduce human error and enhance operational efficiency in the maritime and tourism sectors.

5. References

[1] D. Parekh *et al.*, “A Review on Autonomous Vehicles: Progress, Methods and Challenges,” *Electron.*, vol. 11, no. 14, pp. 1–18, 2022, doi: 10.3390/electronics11142162.

[2] K. Salukh, “70 Persen Kecelakaan Kapal di Indonesia akibat Human Error.” [Online]. Available: https://www.victorynews.id/ntt/3319975829/70-persen-kecelakaan-kapal-di-indonesia-akibat-human-error

[3] J. Terven, D. M. Córdova-Esparza, and J. A. Romero-González, “A Comprehensive Review of YOLO Architectures in Computer Vision: From YOLOv1 to YOLOv8 and YOLO-NAS,” *Mach. Learn. Knowl. Extr.*, vol. 5, no. 4, pp. 1680–1716, 2023, doi: 10.3390/make5040083.

[4] E. Yose, Victor, and N. Surantha, “Portable smart attendance system on Jetson Nano,” *Bull. Electr. Eng. Informatics*, vol. 13, no. 2, pp. 1050–1059, 2024, doi: 10.11591/eei.v13i2.6061.

[5] H. F. Al-Selwi, N. Hassan, H. B. A. Ghani, N. A. B. A. Hamzah, and A. B. A. Aziz, "Face mask detection and counting using you only look once algorithm with Jetson Nano and NVDIA giga texel shader extreme," *IAES Int. J. Artif. Intell.*, vol. 12, no. 3, pp. 1169–1177, 2023, doi: 10.11591/ijai.v12.i3.pp1169-1177.

[6] M. H. Guo *et al.*, "Attention mechanisms in computer vision: A survey," *Comput. Vis. Media*, vol. 8, no. 3, pp. 331–368, 2022, doi: 10.1007/s41095-022-0271-y.

[7] Z. Deng, C. Yao, and Q. Yin, "Safety Helmet Wearing Detection Based on Jetson Nano and Improved YOLOv5," *Adv. Civ. Eng.*, vol. 2023, 2023, doi: 10.1155/2023/1959962.

[8] B. Ma *et al.*, "Distracted Driving Behavior and Driver's Emotion Detection Based on Improved YOLOv8 With Attention Mechanism," *IEEE Access*, vol. 12, pp. 37983–37994, 2024, doi: 10.1109/ACCESS.2024.3374726.

[9] N. F. Abdul Hassan, A. A. Abed, and T. Y. Abdalla, "Face mask detection using deep learning on NVIDIA Jetson Nano," *Int. J. Electr. Comput. Eng.*, vol. 12, no. 5, pp. 5427–5434, 2022, doi: 10.11591/ijece.v12i5.pp5427-5434.

[10] N. F. A. Hassan, A. A. Abed, and T. Y. Abdalla, "Surveillance system of mask detection with infrared temperature sensor on Jetson Nano Kit," *Bull. Electr. Eng. Informatics*, vol. 11, no. 2, pp. 1047–1055, 2022, doi: 10.11591/eei.v11i2.3369.

[11] C. Qi, Z. Wu, L. Wang, H. Feng, and H. Yang, "Artificial intelligence garbage sorting vehicle based on deepstream," *Acad. J. Comput. Inf. Sci.*, vol. 5, no. 13, pp. 82–88, 2022, doi: 10.25236/ajcis.2022.051313.

[12] J. Bedkowski *et al.*, "A novel approach to global positioning system accuracy assessment, verified on lidar alignment of one million kilometers at a continent scale, as a foundation for autonomous driving safety analysis," *Sensors*, vol. 21, no. 17, pp. 1–19, 2021, doi: 10.3390/s21175691.

[13] M. Hussain, "YOLOv1 to v8: Unveiling Each Variant-A Comprehensive Review of YOLO," *IEEE Access*, vol. 12, pp. 42816–42833, 2024, doi: 10.1109/ACCESS.2024.3378568.

[14] A. Ayodeji, M. A. Amidu, S. A. Olatubosun, Y. Addad, and H. Ahmed, "Deep learning for safety assessment of nuclear power reactors: Reliability, explainability, and research opportunities," *Prog. Nucl. Energy*, vol. 151, no. April, p. 104339, 2022, doi: 10.1016/j.pnucene.2022.104339.

[15] I. Usmanov and M. Chernychka, "Maritime Autonomous Weapon Systems from the Standpoint of International Humanitarian Law," *Lex Portus*, vol. 8, no. 2, pp. 33–53, 2022, doi: 10.26886/2524-101X.8.2.2022.2.