 <p>Agreement on the Conservation of Albatrosses and Petrels</p>	<p>Thirteenth Meeting of the Seabird Bycatch Working Group</p> <p><i>Swakopmund, Namibia, 27 - 29 May 2026</i></p> <p>AI Detection of Tori Lines for Seabird Bycatch Mitigation: initial results from Argentinian trawlers</p> <p><i>Candice Untiedt¹, Saqib Muhammad¹, Carlie Devine¹, Geoffrey N. Tuck¹, Leandro L. Tamini², Leandro N. Chavez², Rubén F. Dellacasa², Esteban Frere³ & Yann Rouxel³.</i></p> <p><i>¹The Commonwealth Scientific and Industrial Research Organisation, ²Aves Argentinas, ³BirdLife International Marine Programme.</i></p>
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SUMMARY

Tori lines are crucial for mitigating seabird bycatch and their deployment is mandatory in various fishing hotspots, yet monitoring their usage currently relies on expensive observer programmes and/or labour-intensive manual review of video footage, affecting the effectiveness of compliance monitoring and conservation efforts. The Commonwealth Scientific and Industrial Research Organisation (CSIRO) has successfully demonstrated the feasibility of using deep learning to automate the detection of tori lines, using Electronic Monitoring (EM) footage from tuna longline vessels in Australia (Acharya et al., 2024). In this document, we report on CSIRO's, BirdLife International and Aves Argentinas collaboration to test and improve the deep learning (AI) tori line model using footage from Argentinian industrial trawlers. Applying the pre-trained model on imagery from the Argentinian fishery initially resulted in a low detection rate (True Positives) of 31.1%. Re-annotation and retraining the system on images from the Argentinian fishery significantly increased the detection rate of tori lines to 78.6%. Despite this progress, challenges remain, such as an increase in false positives to 37% caused by linear features of the vessel being mistaken for tori lines. To further improve the precision and accuracy of the model, we aim to increase our training datasets using EM footage from a variety of fisheries across the southern hemisphere. Our long-term goal is to implement real-time Edge AI detection systems on commercial vessels, providing a scalable solution for fisheries management to verify compliance with mandatory tori line deployment and support conservation efforts for threatened seabird species.

1. INTRODUCTION

Effective implementation of Tori lines (TLs) is vital for achieving seabird conservation targets and complying with fishery regulations. However, monitoring compliance currently relies on manual video review or observer reports, which are labour-intensive, and often cover a low percentage of total fishing events. Leveraging artificial intelligence (AI) for automated detection of Tori lines in electronic monitoring (EM) imagery offers a scalable and cost-effective solution to enhance monitoring accuracy, support enforcement, and strengthen the sustainability of fishing practices. The development of robust AI-based detection method and tori line deployment monitoring pipeline will ensure greater transparency and accountability in bycatch mitigation efforts.

2. METHODS

In collaboration with BirdLife International and Aves Argentinas, we evaluated the AI model of Acharya et al. (2024) on a dataset of 4,360 frames extracted from video footage captured by Aves Argentinas aboard one industrial trawler, operating in Argentinian waters between August and September 2021. This imagery included both day and night conditions, varied weather, image quality and different camera angles (Figure 1). Unlike the original training data (Acharya et al., 2024; Figure 2), which had a different field of view for a different fishery, this new dataset included full Tori line assemblies—typically appearing as multiple streamers forming visible sets. To prepare for model evaluation, we inspected each frame for the presence of Tori lines and manually coded this information, identifying 2,100 frames (48.2%) that contained visible Tori lines. The existing model (Acharya et al., 2024) was applied to the Aves Argentinas imagery data and model performance evaluated using model predictions, visualized in the Computer Vision Annotation Tool (CVAT) for each frame, against manually derived validation data.

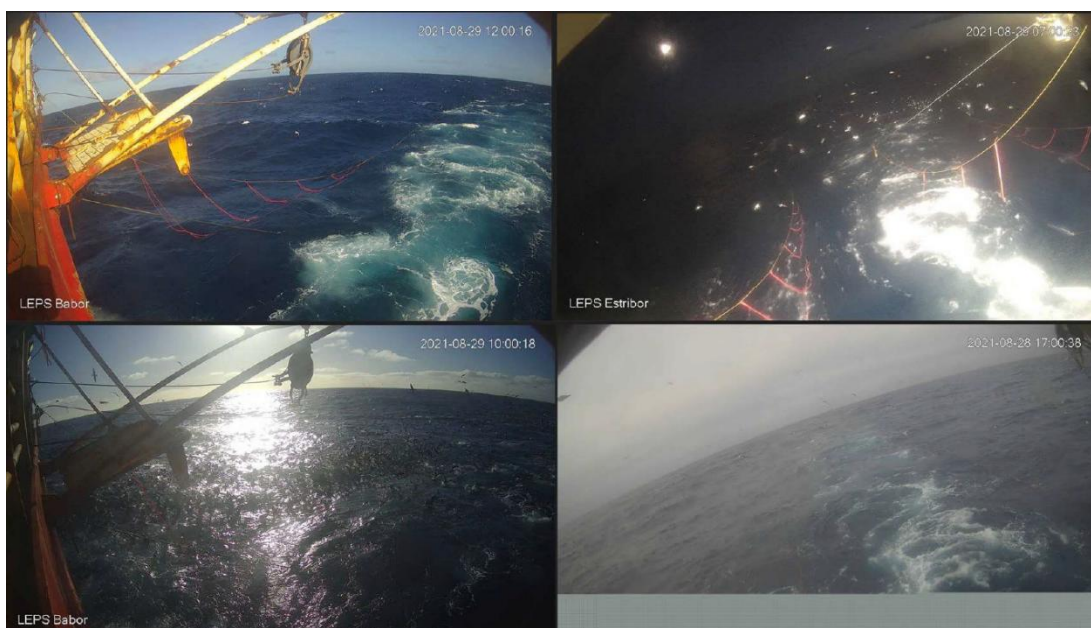


Figure 1. Aves Argentinas imagery data from two trawlers, all containing Tori lines and showing varied conditions (e.g. day, night, glare, faintly visible).

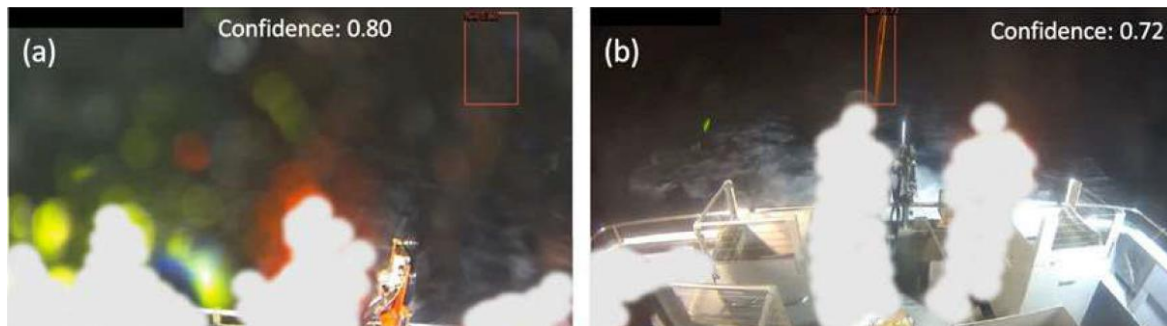


Figure 2. Tori line detections from the model developed by Acharya et al. (2024) showing the different viewpoint of Tori lines from these vessels, compared with the Aves Argentinas imagery (Figure 1).

We then re-trained the model on the Aves Argentinas data using the CVAT platform. Annotations were bounding boxes around entire Tori line sets, with one bounding box per set. On rare occasions when only individual streamer lines were present, these were annotated with a single bounding box. During this process we also reviewed and amended the model's initial predictions, correcting false positives and false negatives. The new training dataset was analysed using the COCO evaluation framework, with all Tori line detections falling into the "large object" category ($> 96 \times 96$ pixels), which typically favours detection performance.

3. RESULTS

The pre-trained model (Acharya et al., 2024) returned 1,108 detections from the 4,360 frames, with only 655 of these being True Positives (Table 1), a detection rate of 31.1%. After reannotation and model retraining on the curated dataset, the detection rate improved, increasing to 78.6%, and the number of False Negatives (missed TL) decreased from 68.9% to 21.4%. The retrained model did, however, suffer from overprediction of TL, with the rate of true negatives decreasing and false positives increasing.

Table 1. Model performance for detections of the pre-trained Tori line model (Acharya et al., 2024) and the re-trained model on BirdLife International imagery (4360 frames).

Tori Line present	Measure	Pre-trained Model %	Re-trained Model %
With Tori line (n=2100)	True positive (detected TL)	31.1%	78.6%
	False negative (missed TL)	68.9%	21.4%
Without Tori line (n=2260)	True negative (correct nondetection)	80.0%	63.0%
	False positive (incorrect detection)	20.0%	37.0%

4. CONCLUSION

While these results demonstrate promising detection capability, there are some challenges to overcome before reaching a desired detection precision of greater than 80%. Notably, the model struggled in frames where Tori lines were faint, partially obscured or not present (False Positives). False Positives also occurred in scenes with linear features that resembled streamer elements (Figure 3).

By enhancing the accuracy and reliability of Tori line detection in EM imagery, this work will support more efficient compliance monitoring and thereby contribute to seabird bycatch reduction and align with global sustainability goals for responsible fisheries management. In addition, combining the AI tori-line detection capability with AI seabird detection and counting models (CSIRO, 2024) has the potential to evaluate the efficiency of tori lines at deterring birds within the protected area.

To improve model performance and scalability, the following next steps would be required:

- **Expanded training data:** Additional annotation of diverse Tori line examples from multiple vessels, including night-time and marginal visibility conditions, to broaden the model's robustness.
- **Model architecture updates:** Evaluation of modern object detection models (e.g. YOLOv8, Faster R-CNN with attention modules) for improved feature extraction from complex scenes.
- **Temporal integration:** Incorporation of short video sequences (rather than single frames) to improve context-aware detection of Tori lines in low-visibility situations.
- **Deployment planning:** Transition from research to application by testing real-time or edge-capable AI detection on vessel-based monitoring systems.

CSIRO, BirdLife International and Aves Argentinas are committed to continue their collaboration to further improve the AI detection tori line model. Pending funding, future projects will seek to secure onboard visual data from a variety of longline and trawl fisheries across the southern hemisphere for the training of the AI model and ultimately build an Edge AI-Detection system for near real-time verification of tori line use on commercial fishing vessels. The aim is to provide a scalable system that has the capability of being operationalised across fisheries and offers fishery managers, authorities and conservationists with reliable information on the mandatory use of tori lines in key global bycatch hotspots.

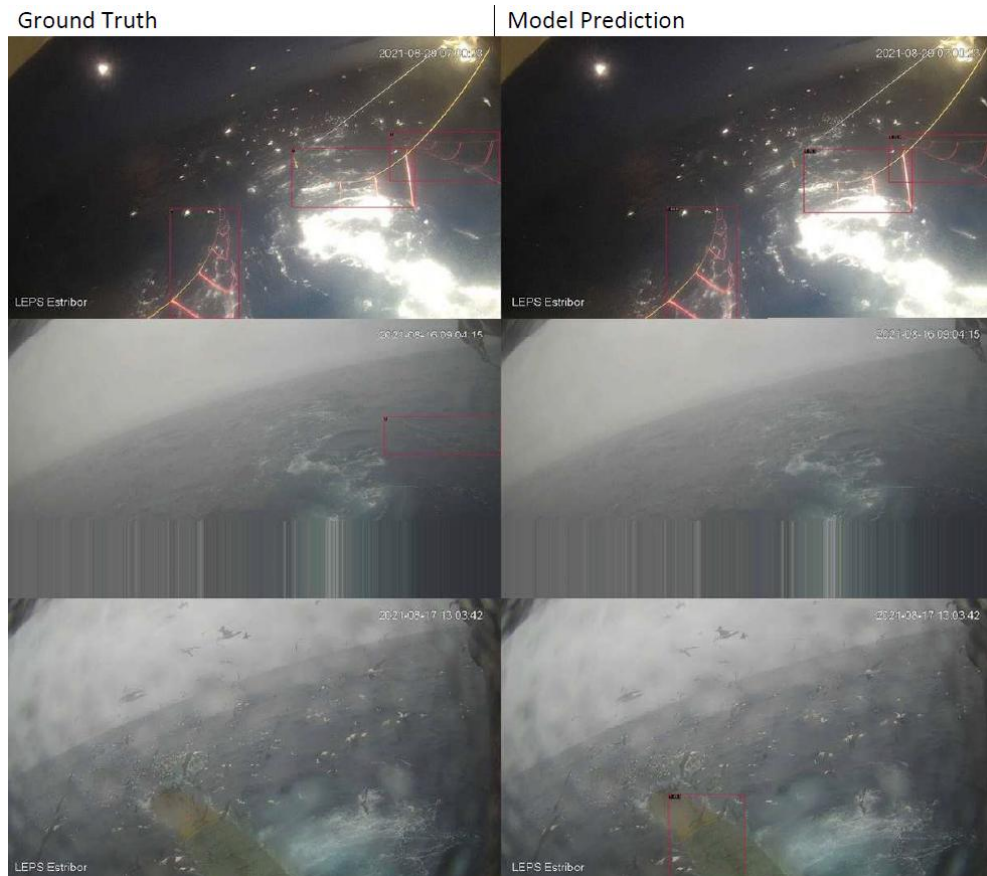


Figure 3. Examples of ground truth annotations and model predictions for *Aves Argentinas* frames showing accurate (top), missed (middle) and incorrect (bottom) Tori Line detections.

5. REFERENCES

Acharya, D. et al. (2024). Using deep learning to automate the detection of bird scaring lines on fishing vessels. *Biological Conservation*. <https://doi.org/10.1016/j.biocon.2024.110713>

CSIRO (2024). [JONATHAN: The SEA-MES On-vessel Automated Seabird Detector – Southeast Australian Marine Ecosystem Survey](#).