Lessons Learned and Implementation Strategy for the Pilot Project 3

Pilot 3 – Autonomous Maritime Systems

Implementation

The implementation of Pilot 3 extended beyond the development and evaluation of individual AI models. The pilot included the collection and preparation of trajectory and environmental datasets, the development and validation of machine learning models for vessel trajectory prediction, and the development of computer vision models for sea-state recognition and small-object detection.

For trajectory forecasting, both probabilistic and machine learning approaches were investigated for short-term and long-term prediction tasks. The developed models were trained and validated using vessel movement data and evaluated under different forecasting horizons.

For sea-state recognition, several state-of-the-art convolutional and transformer-based computer vision architectures were assessed. To address the scarcity of training data for higher sea states, a synthetic data generation methodology was developed, enabling the creation of realistic training images covering a wide range of sea conditions, sun positions, vessel orientations, and wave characteristics.

The pilot further investigated ensemble and multimodal approaches, combining visual information with wind-speed data and introducing temporal aggregation methods to enhance prediction robustness and consistency.

Finally, the trajectory prediction, anomaly detection, sea-state recognition, and small-object recognition capabilities were integrated into an experimental navigation framework. The integrated system was tested in both controlled and real-world scenarios, demonstrating the feasibility of combining behavioural prediction and environmental sensing to support maritime situational awareness and future autonomous navigation functionalities.

Lessons Learned

The pilot generated several important methodological and technical insights.

Trajectory Prediction

- For short-term trajectory forecasting (1-2 seconds), probabilistic approaches proved highly effective. Bayesian models incorporating prior state information consistently outperformed Markov chain models, highlighting the importance of leveraging recent trajectory history for near-term predictions.
- For long-term forecasting, advanced attention-based architectures demonstrated superior performance compared to traditional recurrent neural networks. In particular, the UniTS foundation model achieved the best overall results, indicating the importance of capturing long-range temporal dependencies and contextual information.
- Predicting positional x and y offsets directly was found to be significantly more robust than predicting speed and heading. Speed and heading exhibited high variability and introduced larger prediction errors, whereas direct position-offset prediction produced more stable and accurate results.

Environmental and Contextual Factors

- The inclusion of environmental parameters such as wave height did not significantly improve trajectory prediction performance for the analysed vessels and datasets. This demonstrated that additional features should only be incorporated when they provide measurable predictive value.

Computer Vision and Data Augmentation

- Synthetic data generation proved highly valuable for addressing the lack of training samples for severe sea states. The introduction of synthetic imagery improved test accuracy and mean F1 score by approximately 6% and reduced the maximum classification error from 7 to 3 Beaufort levels compared with training on real data alone.
- Ensemble approaches and multimodal fusion combining image-based predictions with wind-speed information significantly outperformed individual models.
- Temporal voting and prediction aggregation across consecutive frames further improved robustness, reducing the maximum error to 2 Beaufort levels and demonstrating the benefits of exploiting temporal consistency in maritime environmental conditions.

Collaboration and Innovation

- The pilot confirmed the importance of interdisciplinary collaboration between academic and industrial partners. The combination of AI expertise, domain knowledge, and operational experience enabled both methodological innovation and practical validation of the developed solutions.
- Joint benchmarking activities, continuous knowledge exchange, and collaborative development processes contributed significantly to the quality and applicability of the outcomes.

Recommendations

Based on the lessons learned, several recommendations can be made for future research and innovation activities.

Methodological Recommendations

- Continue investigating advanced foundation models and attention-based architectures for long-term trajectory forecasting.
- Explore hybrid approaches that combine probabilistic and machine learning methods to improve prediction accuracy across different forecasting horizons.
- Prioritize direct prediction of positional offsets rather than speed and heading variables when modelling vessel trajectories.

Computer Vision Recommendations

- Further expand the use of synthetic data generation to address data scarcity and improve model generalization.
- Investigate additional sensing modalities and multimodal approaches, particularly for low-visibility and night-time conditions. Potential sources include near-infrared cameras, thermal imaging systems, and other complementary sensors.
- Continue developing ensemble and temporal aggregation techniques to improve prediction robustness and operational reliability.

Data and Validation Recommendations

- Increase the scale and diversity of datasets by incorporating additional vessel types, routes, weather conditions, and operational environments.
- Validate developed models across a broader range of real-world scenarios to assess generalization performance and operational readiness.

Collaboration Recommendations

- Strengthen collaboration between research organizations and industry partners through regular workshops, joint validation activities, and shared analytical frameworks.
- Maintain a co-creation approach throughout the project lifecycle to ensure that scientific advances are translated into practical and operationally relevant solutions.

Overall, the pilot demonstrated the potential of combining advanced AI methodologies, synthetic data generation, multimodal sensing, and interdisciplinary collaboration to support future maritime situational awareness and autonomous navigation systems.