Contextual Maritime Anomaly Detection

Master Thesis Defense

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Outline

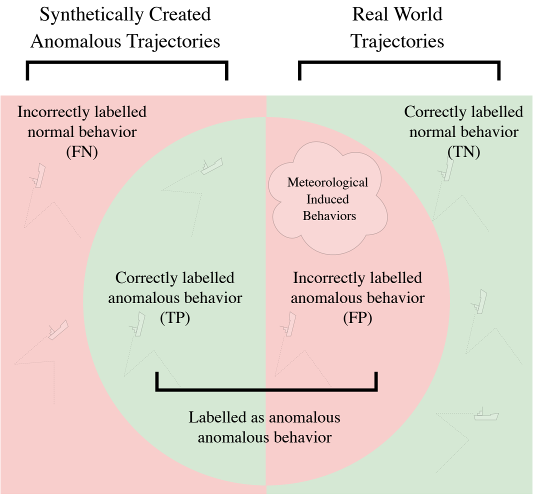
Domain Context

- There exists a significant interdependence between economic prosperity and access to maritime trade [2]
- Consequences of maritime incidents impose significant national risks [1]
- Maritime Situational Awareness (MSA) systems mitigate adverse outcomes of maritime incidents [6, 4]

Problem Statement

- Deep learning approaches for maritime anomaly detection ignore meteorological context
- Weather-induced shipping patterns are flagged as anomalous
- High false positive rates reduce MSA system usability for Vessel Traffic Monitoring staff [5]

Research Rationale



Literature Gap

Literature Gap

Current deep learning anomaly detection approaches inadequately address weather-induced behavior, resulting in high false alarm rates

Research Objective

Main Research Question

How can the integration of meteorological information augment the effectiveness of deep learning approaches in distinguishing weather-induced vessel movements from maritime trajectory anomalies?

Sub-research Objectives

Sub-research Questions (Summarized)

RQ1: Impact of Model Complexity

RQ2: Impact of Meteorological Variables

RQ3: Model Performance by Anomaly Type

RQ4: Model Performance Under Varying Weather Conditions

Data Sources

AIS Data

- US West Coast dataset [3]
- January-September 2023
- 7,340 unique vessel trajectories
- Position, speed, course, timestamp

Meteorological Data

- Fifth generation ECMWF Reanalysis (ERA5)
- Wind components (10m above sea level)
- Wave height, period and direction

Data Integration

Spatial-temporal joining: AIS trajectories enriched with meteorological statistics (μ, σ) per trajectory

Model Architecture

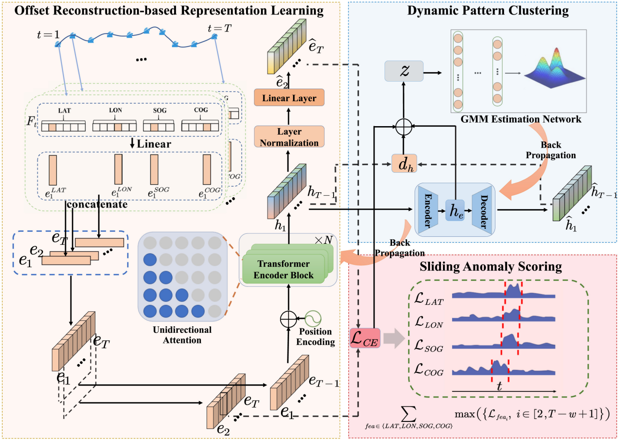


Figure: Model Architecture Adapted from [3]. **Key Enhancement:** Weather statistics (μ, σ) per trajectory integrated into the Dynamic Pattern Clustering component.

Experimental Design I

Metrics

1. ROC AUC Score: overall discriminative capabilities
2. Specificity: true negative rate
3. Sensitivity: true positive rate
4. McNemar's Statistical Test (Specificity)

Experimental Design II

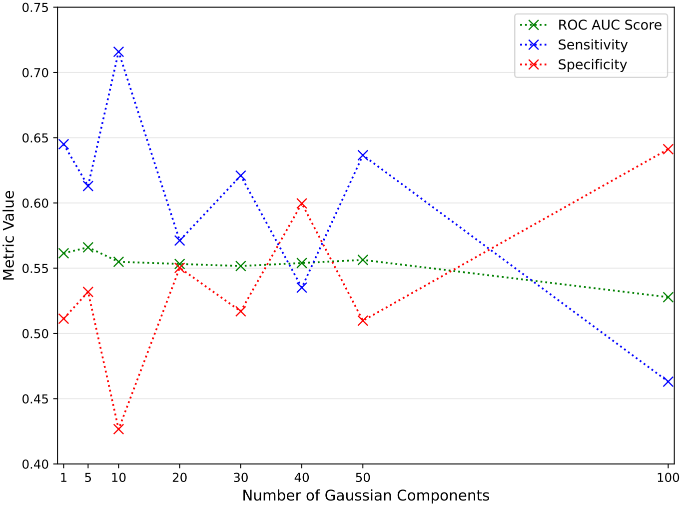
Synthetic Anomaly Types:

1. **Shift Deviation:** Lateral/longitudinal displacements
2. **Abnormal Heading:** Lateral/longitudinal displacements and course over ground deviations
3. **Abnormal Speeding:** Velocity deviations with Gaussian noise

Evaluation Parameters:

- d**:** Spatial deviation
- ρ**:** Proportion of perturbed points per trajectory
- r**:** Ratio of anomalous trajectories (0.1)

RQ1: Optimal GMM Components I



RQ1: Optimal GMM Components II

Key Finding

With added model complexity, ROC AUC Score remains stable; specificity increases at expense of sensitivity.

RQ2: Impact of Meteorological Variables

Table: Weather-Enhanced minus Baseline Model Performance

Setup	**Specificity**	**Sensitivity**	**ROC AUC**
A ($d \in \{0, 1\}$)	+0.0372	-0.0276	-0.0096
B ($d \in \{0, 2\}$)	+0.0574	-0.0617	-0.0161

Key Finding

Consistent improvement in specificity (reduced false alarms)

RQ3: Performance by Anomaly Type

Table: Weather-Enhanced minus Baseline Performance

Anomaly Type	**ROC AUC**	**Sensitivity**	**Specificity**
Shift Deviation	-0.0044	+0.1375	-0.1132
Abnormal Heading	-0.0082	-0.1585	+0.1676
Abnormal Speeding	-0.0161	-0.0617	+0.0574

Key Finding

Synthetic anomalies that have no relation with actual weather-induced behaviors will result in better distinguishability from normal behavior, resulting in less false alarms.

RQ4: Performance Under Weather Severity

Table: High Severity minus Low Severity Weather Conditions

Anomaly Type	ROC AUC	Sensitivity	Specificity
Shift Deviation	+0.0637	-0.0545	+0.1044
Abnormal Heading	+0.1099	+0.2571	-0.0384
Abnormal Speeding	+0.0782	-0.0105	+0.1545
Mean	**+0.0839**	**+0.0640**	**+0.0735**

Key Finding

Weather-enhanced model improves overall discriminative performance under severe weather conditions.

Key Findings Summary

1. **Stable Discriminative Capability:** Overall ROC AUC remains stable with weather integration
2. **Improved Specificity:** Consistent reduction in false positives across experimental setups
3. **Anomaly-Type Dependent:** Reduction of false positives is most effective for heading and speeding anomalies
4. **Weather Severity Resilience:** Enhanced overall discriminative performance during severe weather conditions

Trade-off

Improved specificity (fewer false alarms) comes at the cost of slightly reduced sensitivity (missed anomalies)

Discussion

Implications

- For maritime operations
- For researchers

Limitations

- Geographical scope
- Validation framework

Future Research Directions & Contribution

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Future Research

- Generalizability
- Architecture Optimization
- System Usability

Contribution

- Successfully demonstrated that meteorological data integration in a multi-model deep learning model can significantly improve the ability to distinguish weather-induced vessel movements from anomalies.

The End

Thank you for your attention!

Questions & Additional discussions

Backup: Model Hyperparameters

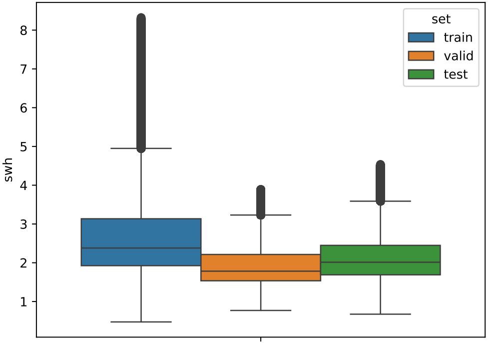
Parameter	Value
Embedding Dimension	32/48
Transformer Heads	8
Transformer Layers	4
Max Sequence Length	10
GMM Components (C)	20/30
Learning Rate	1×10^{-5}
Optimizer	AdamW
Training Epochs	250

Backup: Statistical Significance Tests

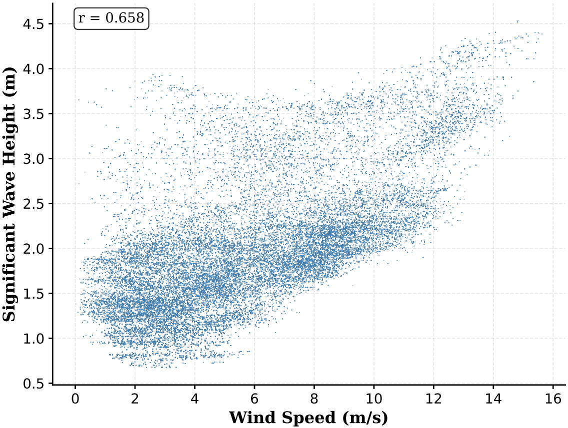
Statistical Significance (McNemar's test, $p < 0.01$):

- ✓ Shift Deviation: $\mathrm{p} = 2.72 \times 10^{-17}$
- ✓ Abnormal Heading: $\mathrm{p} = 8.77 \times 10^{-3}$
- × Abnormal Speeding: $p = 0.332$

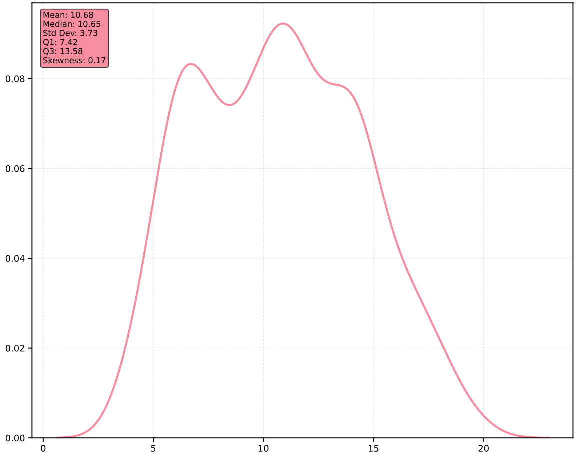
Backup: Test Set Weather Distribution



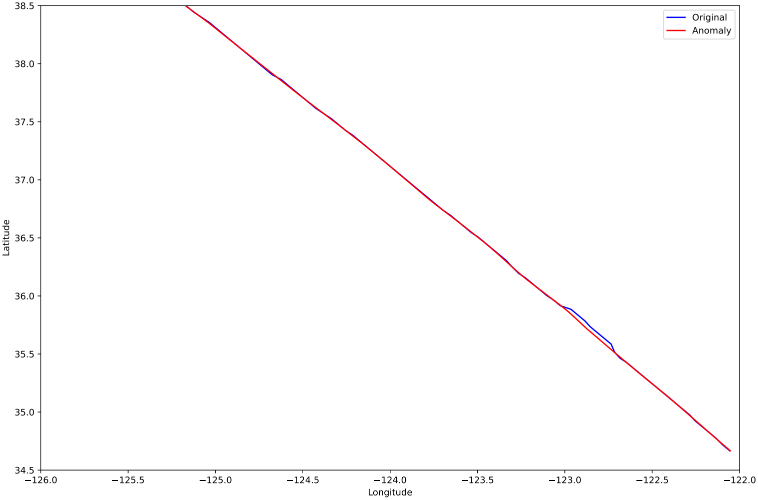
Backup: Relationship Between Wave Height and Windspeed



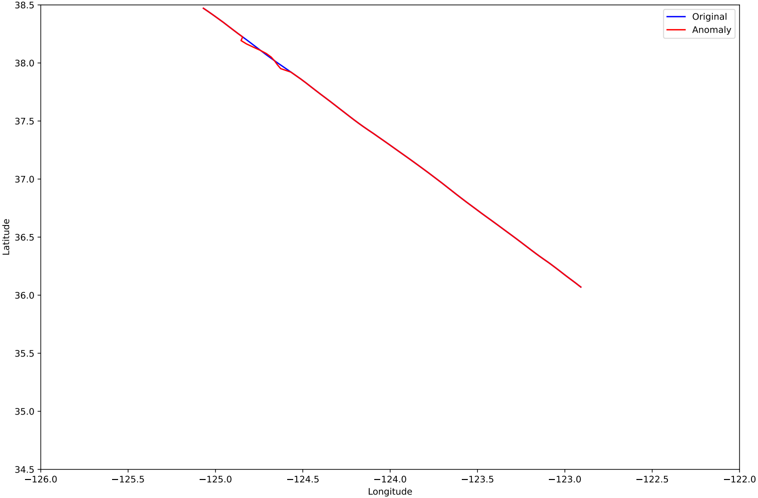
Backup: Aggregated Weather Statistics



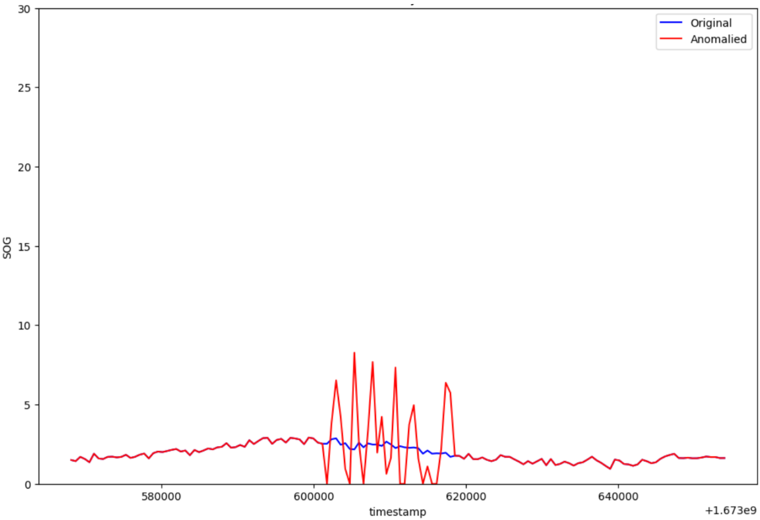
Backup: Synthetic Anomalies I



Backup: Synthetic Anomalies II



Backup: Synthetic Anomalies III



References I

European Maritime Safety Agency.
Annual Overview of Marine Casualties and Incidents 2024.
Annual Overview Ares(2024)8229157, European Maritime Safety Agency, Lisbon, Portugal, june 2024.

Jesse M Lane and Michael Pretes.
Maritime dependency and economic prosperity: Why access to oceanic trade matters.
Marine Policy, 121:104180, 2020.

Hui Li, Wengen Li, Shuyu Wang, Hanchen Yang, Jihong Guan, and Yichao Zhang.
Stad: Ship trajectory anomaly detection in ocean with dynamic pattern clustering.
Ocean Engineering, 313:119530, 2024.

References II

Maohan Liang, Lingxuan Weng, Ruobin Gao, Yan Li, and Liang Du.
Unsupervised maritime anomaly detection for intelligent situational awareness using ais data.
Knowledge-Based Systems, 284:111313, 2024.

Saeed Mehri, Ali Asghar Alesheikh, and Anahid Basiri.
A context-aware approach for vessels' trajectory prediction.
Ocean Engineering, 282:114916, 2023.

Brian Murray and Lokukaluge Prasad Perera.
A dual linear autoencoder approach for vessel trajectory prediction using historical ais data.
Ocean engineering, 209:107478, 2020.