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Generative AI for Smart Maritime Systems: Trajectory Prediction and Navigation Support

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Abstract: Accurate forecasting of vessel movements enhances maritime safety, enables fuel-efficient routing, and supports the development of autonomous ships. Traditional rule-based and statistical methods struggle in dynamic maritime environments, especially when Automatic Identification System (AIS) data contains noise, gaps, or inaccuracies. This paper explores the application of generative AI models—specifically Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs)—for vessel trajectory prediction. Experimental results demonstrate that conditional GANs combined with random forest conditioning reduce average displacement error by approximately 38% compared to baseline LSTM models while delivering probabilistic multi-path forecasts. The study also addresses practical challenges such as real-time latency, training stability, model interpretability, and deployment constraints, offering directions for future intelligent maritime systems that improve decision-making in commercial shipping and naval defence.

Keywords: *Ship trajectory prediction, Generative Artificial Intelligence, AIS, GANs, VAEs*

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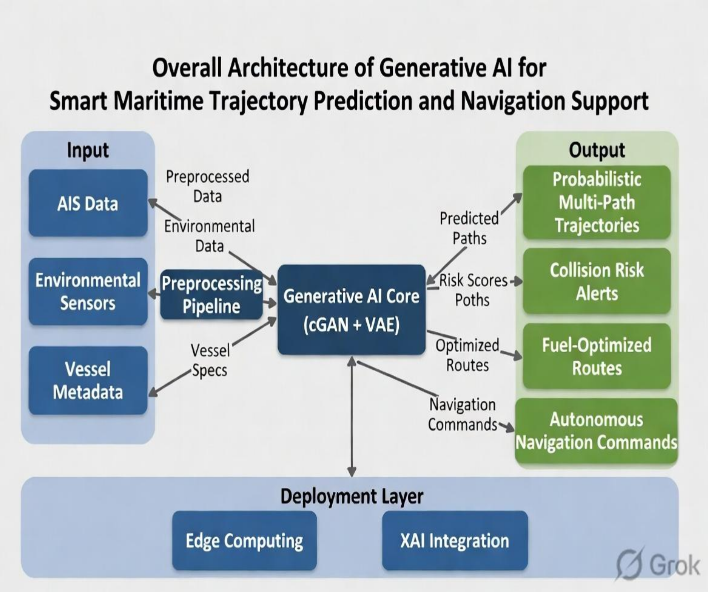
I.INTRODUCTION:

Predicting a vessel's future position and path is essential for safe, efficient, and autonomous maritime operations. The maritime environment is inherently complex, with unpredictable weather, dense traffic, and constantly shifting vessel interactions, demanding models that capture both deterministic patterns and inherent uncertainty.'



The Automatic Identification System (AIS) has transformed vessel monitoring by supplying large-scale, timestamped positional data. While machine learning models such as LSTM and GRU networks have improved prediction accuracy over classical statistical approaches, they typically produce only a single deterministic trajectory and fail to represent the full spectrum of possible routes. Generative AI overcomes these limitations by learning the underlying distribution of navigation behaviours and generating multiple plausible future paths.

This paper presents experimental results from GAN- and VAE-based architectures, details the system design, discusses implementation challenges, and outlines real-world applications and future research directions for intelligent maritime systems.

II.BACKGROUND AND RELATED WORK

2.1 Traditional Methods: Foundations and Limitations

Early navigation relied on celestial observations, compasses, and dead reckoning. Kinematic models based on Newtonian mechanics provided the first analytical predictions:

$$x_{t+\Delta t}=x_t+v\Delta t\cos\theta \quad y_{t+\Delta t}=y_t+v\Delta t\sin\theta$$

where $v$is vessel speed, $\theta$is heading, and $\Delta t$is the time step. Although lightweight and interpretable, these models degrade rapidly under acceleration, course changes, or external forces.

The Kalman filter improved predictions through recursive Bayesian estimation:

Prediction: $\hat{x}_k^-=A\hat{x}_{k-1}+Bu_{k-1} \quad P_k^-=AP_{k-1}A^T+Q$

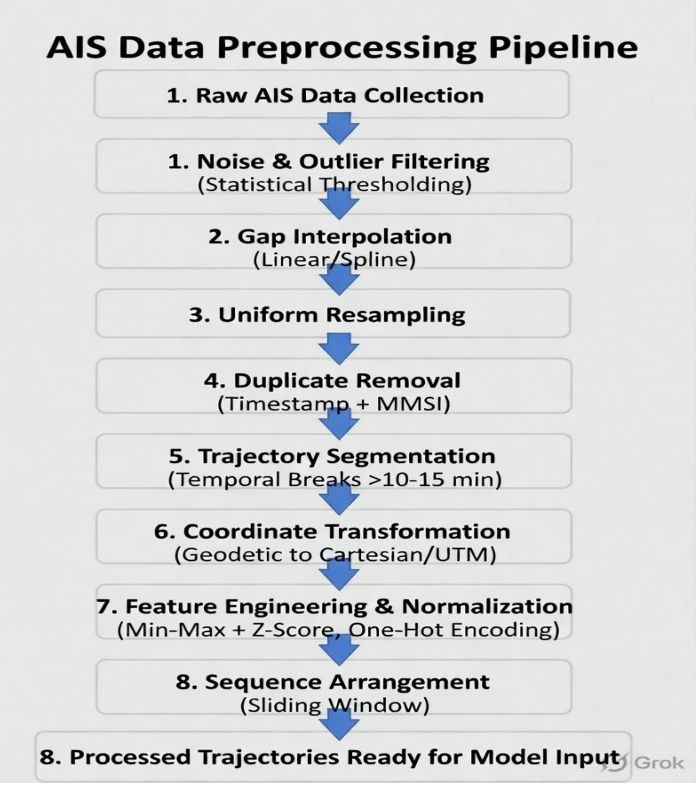
Update:
$K_k=P_k^-H^T(HP_k^-H^T+R)^{-1} \quad \hat{x}_k=\hat{x}_k^-+K_k(z_k-H\hat{x}_k^-) \quad P_k=(I-K_kH)P_k^-$

Extensions such as the Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), and particle filters address nonlinear dynamics. Hidden Markov Models (HMMs) have been used for regular routes. However, purely statistical methods remain limited in handling sudden manoeuvres or missing sensor data. Deep learning has largely superseded these approaches since 2019, with traditional models now serving mainly as benchmarks.

2.2 AIS Data: Structure, Quality, and Preprocessing

AIS broadcasts static vessel information and dynamic positional updates at intervals ranging from seconds to minutes, generating millions of records daily. Public datasets are available from sources such as MarineCadastre.gov and the Norwegian Coastal Administration. Despite wide coverage, AIS data frequently suffers from noise, GPS errors, missing values, duplicates, inconsistent sampling, and deliberate spoofing.

A robust preprocessing pipeline is therefore essential:



This pipeline applied to the Norwegian Coastal Administration dataset yields over 500,000 high-quality vessel trajectories.

2.3 Deep Learning Sequence Models

AIS data's sequential nature suits recurrent architectures. Standard RNNs suffer from vanishing/exploding gradients. LSTMs mitigate this via input, forget, and output gates, enabling effective modelling of long-term dependencies. GRUs offer a lighter alternative with comparable performance. Advanced hybrids (bi-directional LSTMs, CNN-LSTM, Transformer-based models like TrajFormer) further improve accuracy. Nevertheless, these models remain computationally intensive, data-sensitive, and limited to single deterministic forecasts.

2.4 Generative AI Models

Generative models learn the full distribution of possible trajectories, producing diverse future paths critical for risk assessment and collision avoidance.

Conditional GAN (cGAN) The generator and discriminator are trained adversarially. Conditioning on past AIS data, vessel type, and weather enables context-aware trajectory generation with high temporal coherence and physical realism.

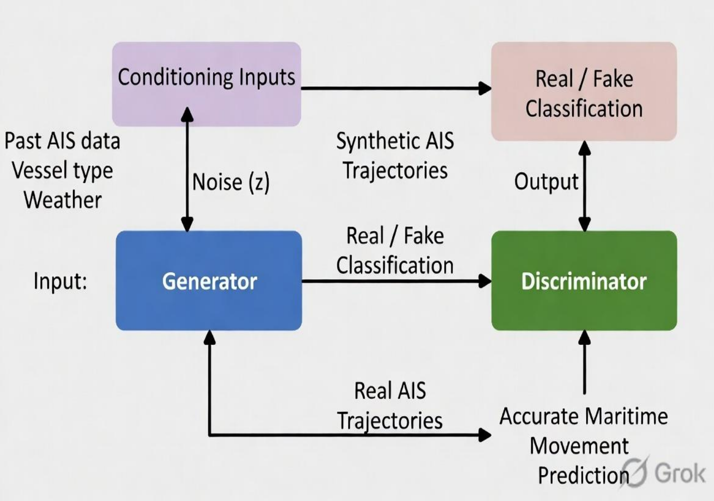
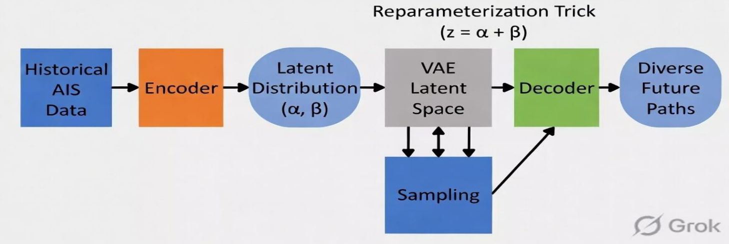


Figure 1: Conditional GAN Architecture for Maritime Trajectory Prediction

Variational Autoencoder (VAE) The encoder compresses trajectories into a latent probabilistic distribution (mean and variance). The reparameterization trick enables differentiable sampling, allowing the decoder to generate multiple coherent paths while quantifying uncertainty. VAEs offer stable training and interpretable latent spaces, though they tend to produce smoother outputs than GANs.

Figure 2: VAE Architecture for Trajectory Generation



Both models are evaluated using displacement errors as well as diversity and distributional similarity metrics.

III.EXPERIMENTAL AND RESULTS.

3.1 Experimental Setup AIS data from U.S. MarineCadastre.gov and the Norwegian Coastal Administration were enriched with Copernicus Marine Service environmental variables (wind, currents, wave height). After preprocessing, an 80/10/10 stratified split by vessel type prevented data leakage. Models were implemented in PyTorch and TensorFlow on an NVIDIA RTX 3060 GPU using the Adam optimizer, batch size 64, dropout, and early stopping.

3.2 Evaluation Metrics

- **Average Displacement Error (ADE):** ADE=$\frac{1}{T}\sum_{t=1}^{T} \| \hat{p}_t - p_t \|$
- **Final Displacement Error (FDE):** FDE=$\| \hat{p}_T - p_T \|$
- **Root Mean Square Error (RMSE):** RMSE=$\sqrt{\frac{1}{T}\sum_{t=1}^{T} (\hat{p}_t - p_t)^2}$ Diversity metrics quantify spread among generated samples.

3.3 Results

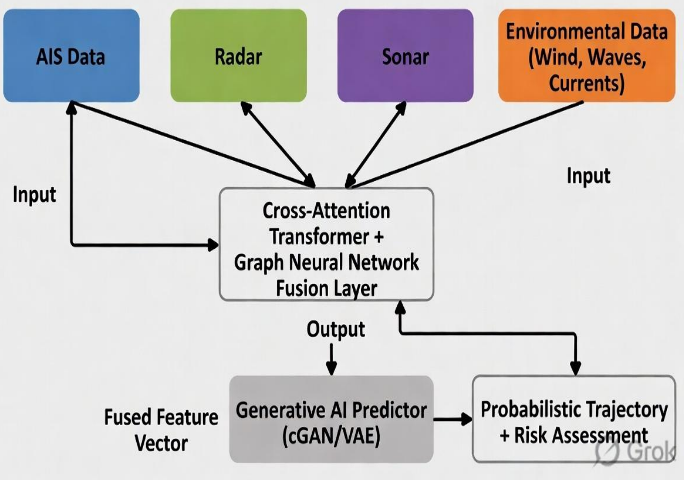
Model	**ADE (m)**	**FDE (m)**	**RMSE (m)**
Polynomial Regression	123.6	210.5	148.3
LSTM	68.2	122.4	89.1
Conditional GAN (cGAN)	41.9	73.8	54.6

Table 2: Model performance comparison. cGAN achieves ~38% ADE and ~40% FDE improvement over LSTM. Qualitative analysis shows cGAN trajectories are smoother and more navigationally consistent, particularly in congested waters. Minor performance drops for tugs and fishing vessels suggest the need for additional behavioural conditioning.

IV.SENSOR FUSION AND DEPLOYMENT CHALLENGES

4.1 Multi-Modal Sensor Fusion AIS alone is insufficient; fusing radar, sonar, and environmental data via multi-modal transformers and graph neural networks creates a unified feature representation for more robust predictions.

Figure 3: Multi-Modal Sensor Fusion Architecture



4.2 Real-World Deployment Challenges Key issues include real-time data cleaning, limited onboard compute (addressed via pruning, quantization, and early-exit networks), and seamless integration with legacy navigation systems.

4.3 Ethical, Legal, and Safety Considerations Explainable AI (XAI), COLREGs compliance, privacy, cybersecurity, and audit logging are mandatory for trustworthy deployment.

V. REAL-WORLD APPLICATIONS

5.1 Commercial Shipping and Port Operations Applications include optimized port traffic management, fuel-efficient voyage planning (up to 15% cost reduction), proactive collision avoidance, fleet ETA prediction, and insurance risk assessment.

5.2 Naval Defence and Coast Guard Operations Generative models enable proactive interdiction, maritime situational awareness (MSA), search-and-rescue trajectory drift prediction, anomaly detection, and autonomous USV navigation.

5.3 Environmental Monitoring and Compliance Trajectory modelling supports emission control zone enforcement, marine protected area intrusion prevention, oil-spill source identification, and whale-habitat risk reduction.

5.4 Autonomous and Smart Shipping Self-navigating vessels, shore-based digital twins, bottleneck traffic optimisation (e.g., Strait of Malacca), and exclusion-zone alerts around offshore platforms become feasible.

VI.FUTURE RESEARCH DIRECTIONS

6.1 Hybrid Model Architectures VAE-GAN hybrids augmented with transformers and graph neural networks will better model multi-vessel interactions and behavioural diversity.

6.2 Reinforcement Learning Integration Combining generative forecasts with multi-agent RL enables adaptive route planning and coordinated defence operations.

6.3 Edge Computing and Lightweight Optimization Pruning, quantization, knowledge distillation, and federated learning will enable efficient onboard deployment.

6.4 Advanced Sensor Fusion Physics-informed neural networks and robust multi-modal architectures will improve performance under adversarial conditions.

6.5 Explainability, Safety, and Compliance Embedding XAI, certifiable safety frameworks, and stakeholder governance will accelerate responsible adoption.

VII.CONCLUSION

Conditional GANs substantially outperform traditional kinematic, statistical, and LSTM baselines for maritime trajectory prediction, delivering a 38% reduction in ADE and 40% in FDE while providing probabilistic multi-path forecasts. The models demonstrate practical viability for real-time inference and robustness across sea conditions. When combined with multi-modal sensor fusion, edge optimisation, and explainable AI, generative approaches will augment human operators, enhance situational awareness, and shape the future of commercial shipping and naval defence. Continued multidisciplinary efforts addressing data quality, computational constraints, legacy integration, and regulatory compliance will be essential for widespread operational deployment.

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