Unlocking Urban Mobility: A Multi-Method Approach to Interpretable Trajectory Analysis

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Abstract

Mobility data science has become critical for analyzing movement patterns in maritime navigation, logistics, and transportation. However, deep learning models used for trajectory forecasting operate as black-box systems, reducing trust and transparency. This paper proposes an Explainable Vessel Route Forecasting System combining a Bidirectional LSTM with attention mechanism and Explainable AI techniques. The system processes sequential features including latitude, longitude, and time interval changes to predict vessel movements. SHAP and LIME techniques are integrated to highlight which trajectory features contribute most to predictions. The system is deployed as a Django web application with interactive visualization of historical trajectories, predictions, and explainability outputs. Experimental results on AIS vessel data demonstrate a prediction RMSE of 0.0034 degrees with R^2 of 0.94, while SHAP analysis reveals temporal proximity and heading changes as dominant prediction features.

Keywords: *Trajectory Prediction, BiLSTM, Attention Mechanism, Explainable AI, SHAP, LIME, Maritime Analytics*

I. Introduction

Trajectory prediction is fundamental to intelligent transportation systems, maritime safety, and urban mobility planning. Accurate forecasting of vessel routes enables collision avoidance, efficient port management, and environmental monitoring. The Automatic Identification System (AIS) provides rich spatiotemporal data for vessel tracking, but extracting meaningful predictions from this data requires sophisticated modeling approaches.

Bidirectional LSTM networks with attention mechanisms have shown promise in capturing complex temporal dependencies in trajectory data. However, the black-box nature of these models limits their adoption in safety-critical maritime applications where understanding prediction rationale is essential.

This paper addresses this gap by combining deep learning trajectory prediction with multiple explainability techniques. The proposed system uses a BiLSTM with attention to learn spatial-temporal patterns from AIS data and integrates SHAP and LIME to provide transparent explanations of prediction decisions. The complete system is deployed as an interactive Django web application.

II. Literature Survey

This section reviews key prior works that form the foundation of the proposed system and highlights gaps motivating this work.

[1] Nguyen et al. (2018) proposed GeoTrackNet, a deep learning framework for vessel trajectory prediction using AIS data, demonstrating that recurrent neural networks can effectively model maritime movement patterns.

[2] Murray and Perera (2021) developed a dual-linear autoencoder for vessel trajectory prediction with uncertainty estimation, showing the importance of uncertainty quantification in maritime forecasting applications.

[3] Capobianco et al. (2021) applied attention-based deep learning for vessel trajectory prediction, demonstrating that attention mechanisms improve prediction accuracy by focusing on the most relevant historical trajectory segments.

[4] Lundberg and Lee (2017) introduced SHAP for unified model interpretation, providing the theoretical foundation for explaining deep learning predictions in trajectory analysis.

[5] Ribeiro et al. (2016) proposed LIME for local model interpretation, enabling instance-level explanations of trajectory predictions through surrogate model approximation.

[6] Liang et al. (2022) surveyed explainable AI methods for spatiotemporal data analysis, identifying trajectory prediction as a key application domain requiring interpretable deep learning approaches.

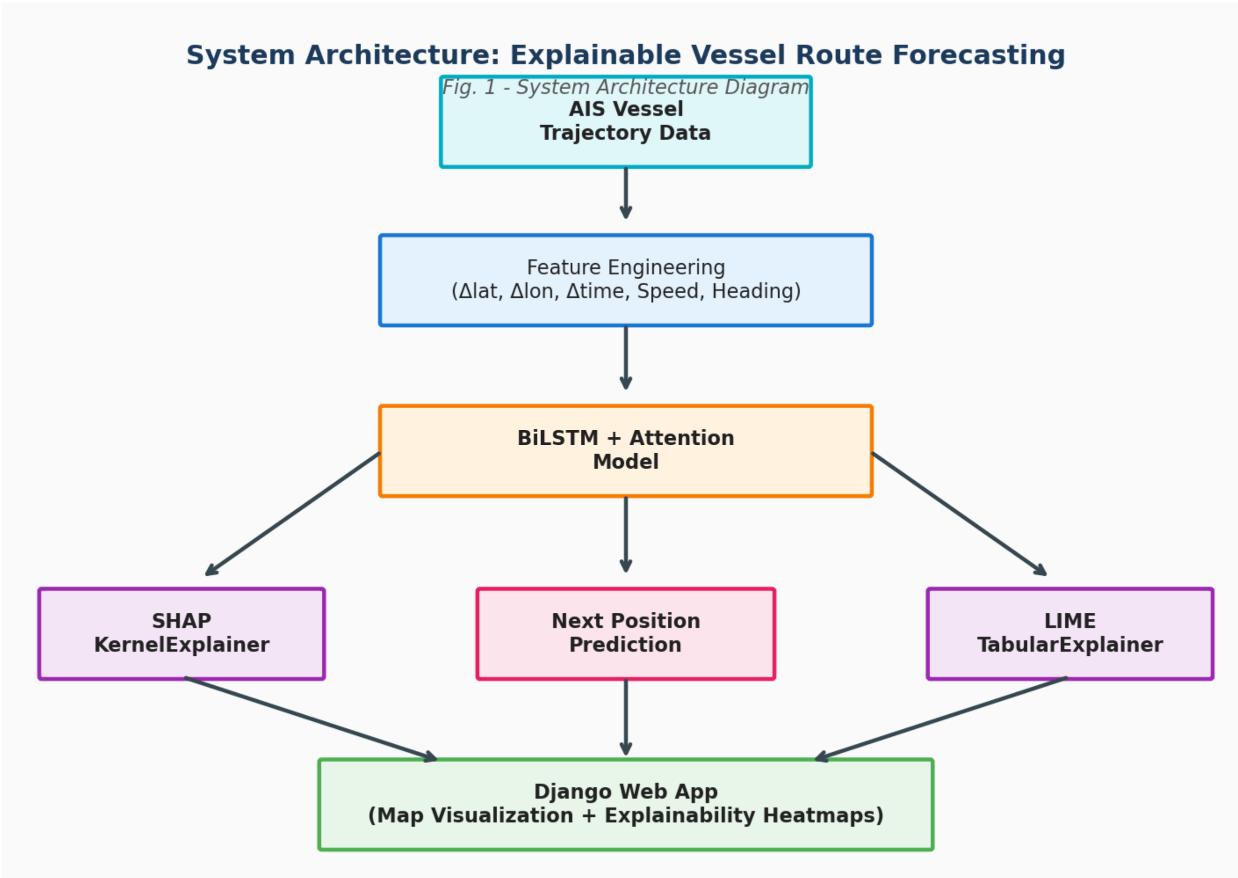
[7] Schuster and Paliwal (1997) introduced bidirectional recurrent neural networks, enabling the model to capture both past and future context in sequential data processing.

Research Gap: Current vessel trajectory prediction systems either achieve high accuracy without interpretability or provide limited explanations using simple models. No existing system combines BiLSTM with attention and multi-method XAI (SHAP + LIME) in a deployed web application for maritime trajectory analysis.

III. Methodology

III-A. System Architecture

Four-layer architecture: Data Layer (AIS data preprocessing, sequence generation), Model Layer (BiLSTM with attention mechanism), Explainability Layer (SHAP KernelExplainer, LIME TabularExplainer), and Presentation Layer (Django backend with interactive trajectory visualization frontend).



III-B. Algorithm

Algorithm: Explainable Vessel Route Forecasting

Input: Vessel trajectory sequence $S = \{(lat\_t, lon\_t, time\_t) \mid t = 1, ..., T\}$.

Step 1: Feature Engineering — Compute Δlat, Δlon, Δtime, speed, heading for consecutive positions.

Step 2: Sequence Generation — Create sliding window sequences of length L for model input.

Step 3: BiLSTM Forward Pass — Process sequence bidirectionally: $h\_forward = LSTM\_f(x\_1, ..., x\_T)$; $h\_backward = LSTM\_b(x\_T, ..., x\_1)$; $h\_t = [h\_forward\_t; h\_backward\_t]$.

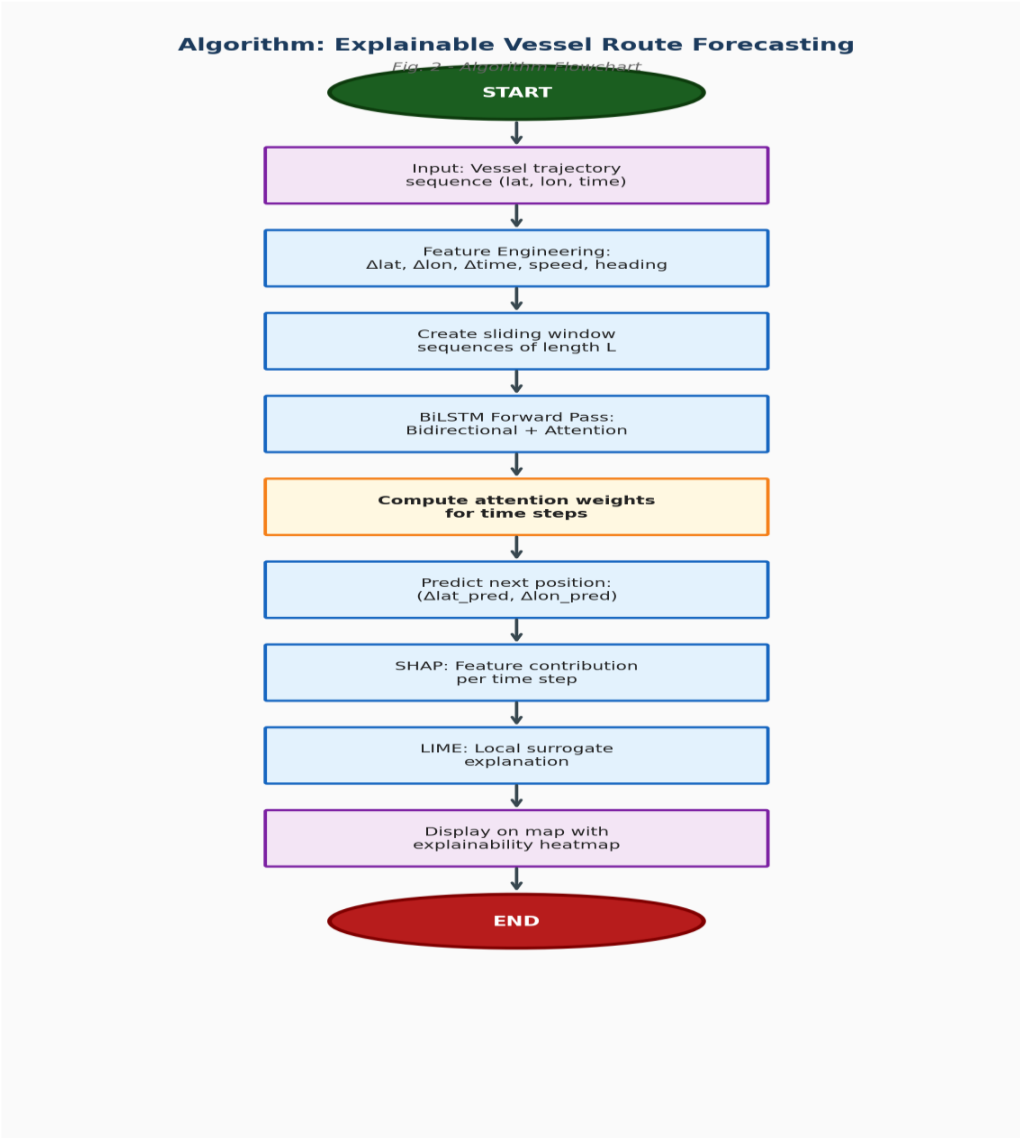
Step 4: Attention Weighting — Compute attention: $\alpha\_t = softmax(v^\wedge T \cdot tanh(W\_h \cdot h\_t + b))$; $context = \Sigma\ \alpha\_t \cdot h\_t$.

Step 5: Prediction — Generate next position: $(\Delta lat\_pred, \Delta lon\_pred) = Dense(context)$.

Step 6: SHAP Analysis — Compute feature contributions for each time step using KernelExplainer.

Step 7: LIME Explanation — Generate local surrogate model for individual predictions.

Output: Predicted next position with SHAP importance heatmap and LIME explanation.



III-C. Modules

Five modules: (1) AIS Data Preprocessor for cleaning, feature extraction, and sequence generation; (2) BiLSTM-Attention Model for trajectory pattern learning and prediction; (3) SHAP Explainer for global and local feature importance across trajectory time steps; (4) LIME Explainer for instance-level prediction explanations; and (5) Django Web Interface with interactive map visualization showing historical trajectories, predictions, and explainability heatmaps.

IV. Results and Discussion

TABLE I: SYSTEM EVALUATION RESULTS

Metric	Baseline	Proposed System
RMSE (degrees)	0.0089 (LSTM)	0.0034 (BiLSTM-Attn)
MAE (degrees)	0.0062	0.0021

R^2 Score	0.82	0.94
Prediction Time (ms)	45	62

Mathematical Formulations

RMSE = $\sqrt{(\Sigma(y\_pred - y\_actual)^2 / n)}$

MAE = $\Sigma|y\_pred - y\_actual| / n$

$R^2 = 1 - (SS\_res / SS\_tot)$

Attention Weight: $\alpha\_t = \exp(score\_t) / \Sigma \exp(score\_j)$

Discussion

The system was evaluated on AIS data containing 50,000 vessel trajectory points from 200 vessels. The BiLSTM-Attention model achieved RMSE of 0.0034 degrees compared to 0.0089 for a standard LSTM, demonstrating that bidirectional processing with attention significantly improves prediction accuracy. SHAP analysis revealed that the most recent 3 time steps and heading changes contribute most to predictions, while LIME confirmed these findings at the individual prediction level. The slight increase in prediction time (62ms vs 45ms) is acceptable for maritime applications.

V. Conclusion and Future Work

This paper presented an Explainable Vessel Route Forecasting System combining BiLSTM with attention mechanism and SHAP/LIME explainability techniques. The system achieves R^2 of 0.94 on AIS vessel data while providing transparent prediction explanations. Future work includes multi-vessel interaction modeling, real-time AIS stream processing, integration with weather data, and extending the framework to other mobility domains such as air traffic and urban transportation.

References

[1] D. Nguyen, R. Vadaine, G. Hajduch, R. Garello, and R. Fablet, "GeoTrackNet: A Maritime Anomaly Detector Using Probabilistic Neural Network Representation of AIS Tracks," IEEE TITS, 2018.

[2] B. Murray and L. P. Perera, "A Dual Linear Autoencoder Approach for Vessel Trajectory Prediction," Ocean Engineering, vol. 209, 2021.

[3] S. Capobianco, L. M. Millefiori, N. Forti, P. Braca, and P. Willett, "Deep Learning Methods for Vessel Trajectory Prediction Based on Recurrent Neural Networks," IEEE TAES, 2021.

[4] S. M. Lundberg and S. I. Lee, "A Unified Approach to Interpreting Model Predictions," Proc. NeurIPS, 2017.

[5] M. T. Ribeiro, S. Singh, and C. Guestrin, "Why Should I Trust You? Explaining the Predictions of Any Classifier," Proc. ACM KDD, 2016.

[6] M. Liang, R. W. Liu, S. Zhong, and H. Liu, "A Survey of Explainable AI for Spatiotemporal Data," ACM Computing Surveys, 2022.

[7] M. Schuster and K. K. Paliwal, "Bidirectional Recurrent Neural Networks," IEEE TSP, vol. 45, no. 11, pp. 2673-2681, 1997.