Extreme weather events in Arctics monitoring and prediction

TEAM 25

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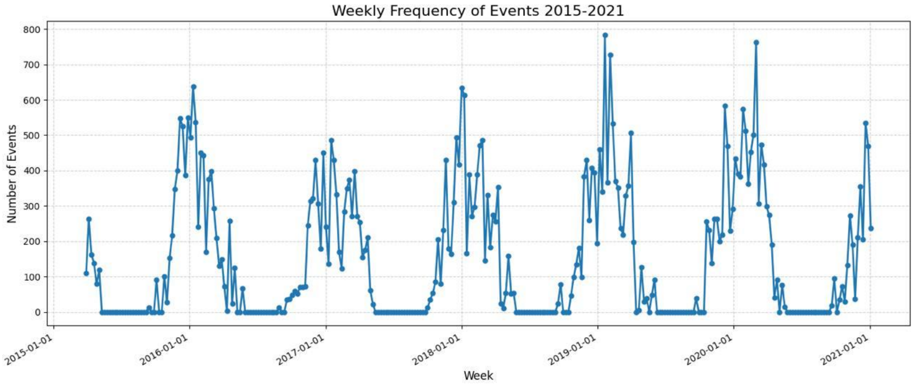
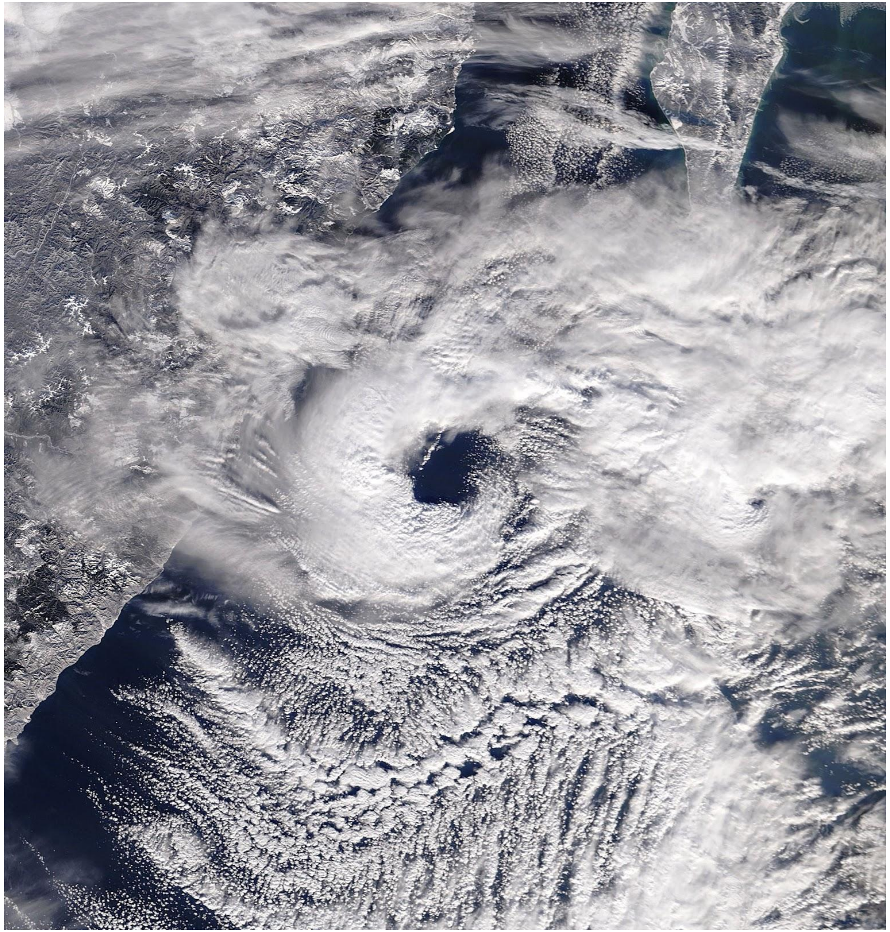
Polar lows

- ❑ Polar lows are intense, short-lived cyclonic systems
- ❑ Significant challenges for forecasting due to their rapid evolution and small spatial scale
- ❑ Detection and prediction of those are crucial for improving maritime safety and understanding Arctic atmospheric dynamics





Experiment

Annotation → Detection → Event Extraction → Trajectory Modeling

Detection of polar low events

Trajectory modeling

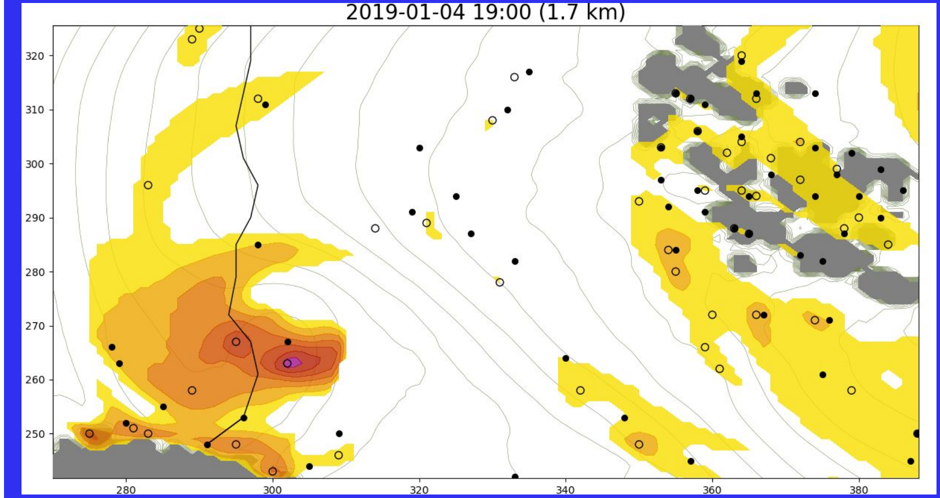
Annotation Methodology

- We manually labeled polar lows and non-events to establish a reliable ground truth for training and validating our models.

- What Was Labeled:
  - Mature-stage polar lows (~10 timestamps)
  - Non-events (~10 timestamps) for balanced classification

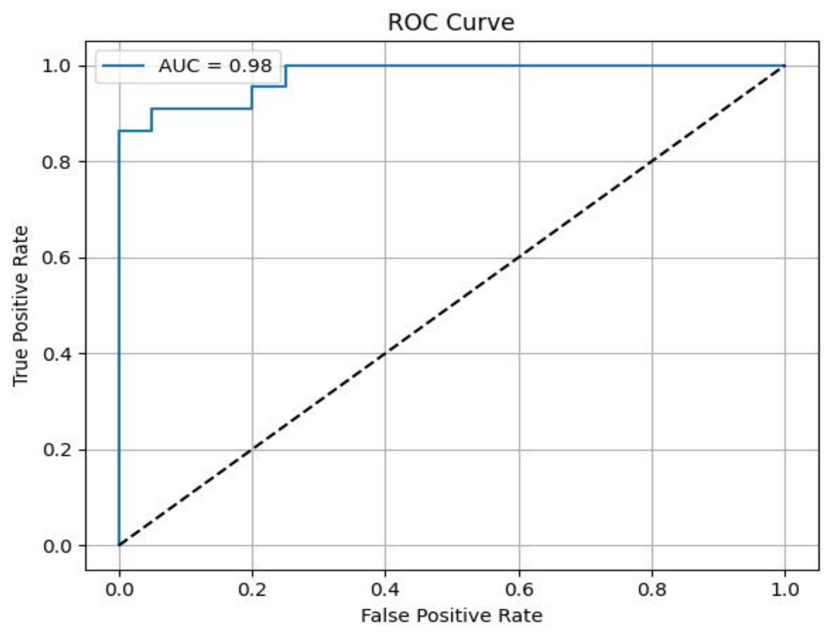
- Tools Used: EddyClicker

- Annotation Criteria:
  - Clear cyclonic eye in WSPD graph
  - Deep purple color in EddyClicker vortices criteria



EddyClicker Software's Interface: black line highlights track of a Polar low, where the x and y axes are the horizontal and vertical coordinates

Detection



- CNN was employed to detect polar low events
  - Loss Function (Binary Cross Entropy)
  - Adam optimizer
  - Batch Size
  - Epochs
  - Early Stopping

Results:

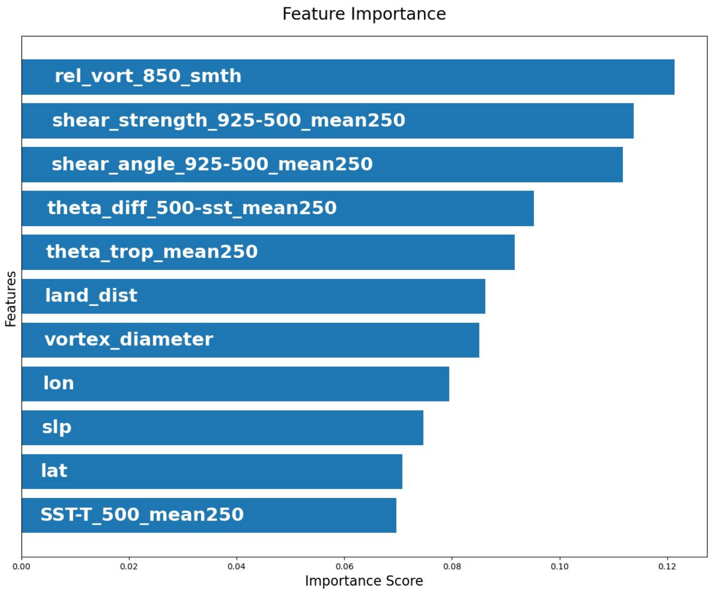
Metric	Value
Accuracy	0.86
Precision (Event)	0.79
Recall (Event)	1.00
F1-Score (Event)	0.88
AUC-ROC	0.98

Trajectory Modeling

Feature	Description
rel_vort	Smoothed relative vorticity at 850 hPa.
vortex_diam	Approximate size of the vortex.
theta_trop, theta_diff	Tropospheric stability and surface–mid-level temperature differences.
shear_angle, shear_strength	Wind shear parameters capturing vertical velocity gradients.
slp, sst_t500	Sea-level pressure and surface–mid-level temperature differences.
land_dist	Distance from land, accounting for land–sea contrasts.
lat, lon	Core geospatial coordinates.

I. Initial approach: *polynomial extrapolation*

II. Refined approach: *recurrent architectures*



Trajectory Modeling

GRU model

I. Masking layer
II. Three GRU layers (128, 96, and 64 units)
   A. Layer normalization and a dropout layer
III. Two dense layers
   A. ReLU

LSTM model

I. Masking layer
II. Bidirectional LSTM layer (128 units)
III. Layer Normalization, Dropout
IV. Additional LSTM layers (96, 64 units) and Dropout layers
V. Dense layer
   A. ReLu

Transformers

I. Multi-head self-attention mechanism (4 heads)
II. Normalization layer
III. Two fully connected layers with expansion
   A. Swish activation
IV. L1 regularization
V. Haversine loss

$$Y_t = (\Delta\text{lat}_t, \Delta\text{lon}_t) = f(X_1, X_2, \ldots, X_t)$$

$$\Delta\text{lat}_t = \text{lat}_t - \text{lat}_{t-1}, \quad \Delta\text{lon}_t = \text{lon}_t - \text{lon}_{t-1}, \quad \text{for } t \geq 1$$

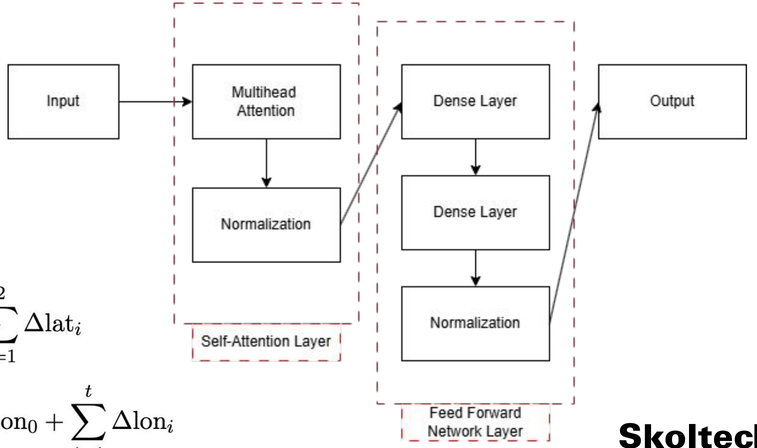
At $t = 0$, no previous position exists, so we set:

$$\Delta\text{lat}_0 = 0, \quad \Delta\text{lon}_0 = 0$$

$$\text{lat}_1^{\text{pred}} = \text{lat}_0 + \Delta\text{lat}_1$$

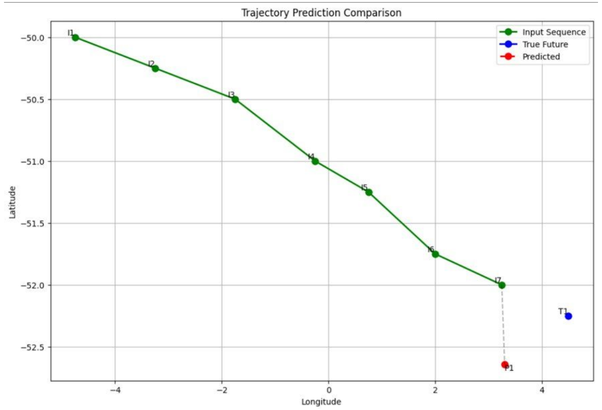
$$\text{lat}_2^{\text{pred}} = \text{lat}_1^{\text{pred}} + \Delta\text{lat}_2 = \text{lat}_0 + \sum_{i=1}^{2} \Delta\text{lat}_i$$

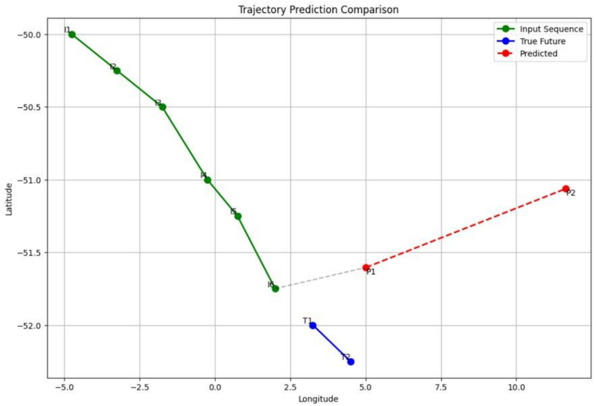
$$\text{lat}_t^{\text{pred}} = \text{lat}_0 + \sum_{i=1}^{t} \Delta\text{lat}_i \quad \text{and} \quad \text{lon}_t^{\text{pred}} = \text{lon}_0 + \sum_{i=1}^{t} \Delta\text{lon}_i$$

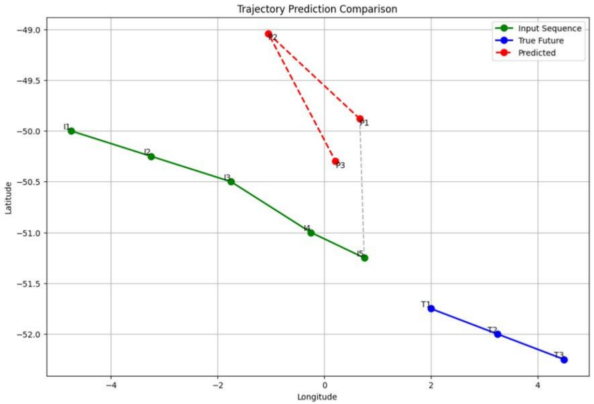


Trajectory Modeling

2 points predicted (trained on 6)

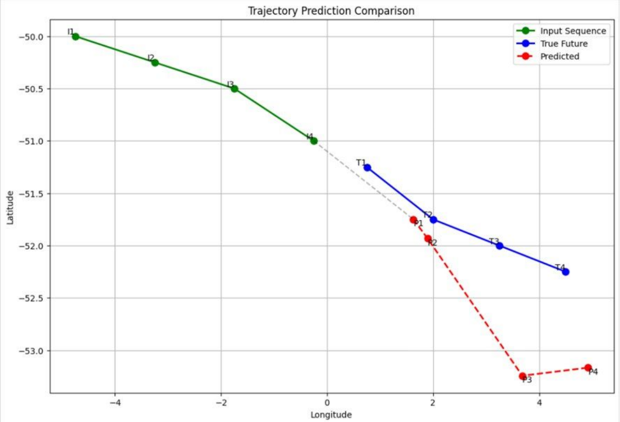






1 point predicted (trained on 7)

3 points predicted (trained on 5)



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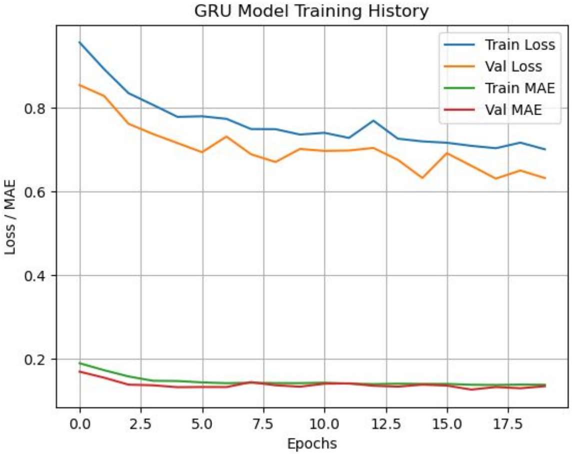
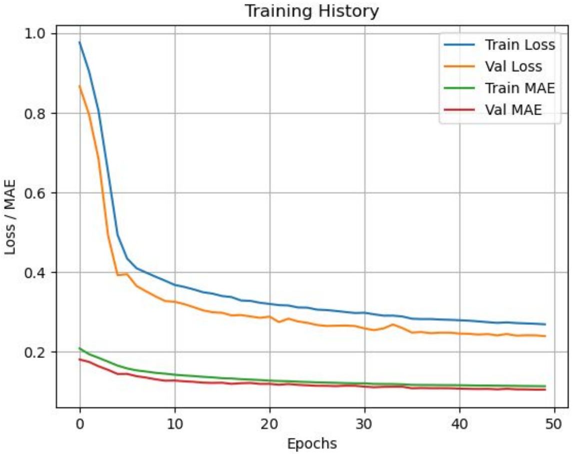
4 point predicted (trained on 4)

Trajectory Modeling

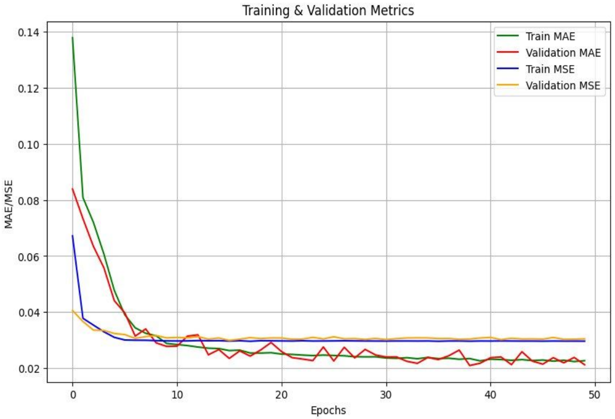
GRU model



LSTM model



Transformers



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Results of the work

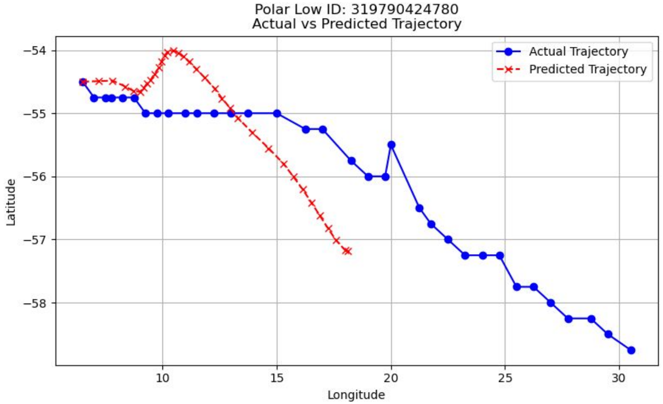

Figure shows the track by GRU model

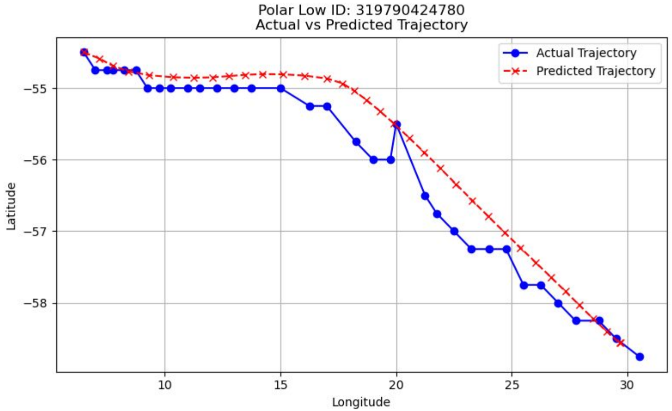

Figure shows the track by LSTM model

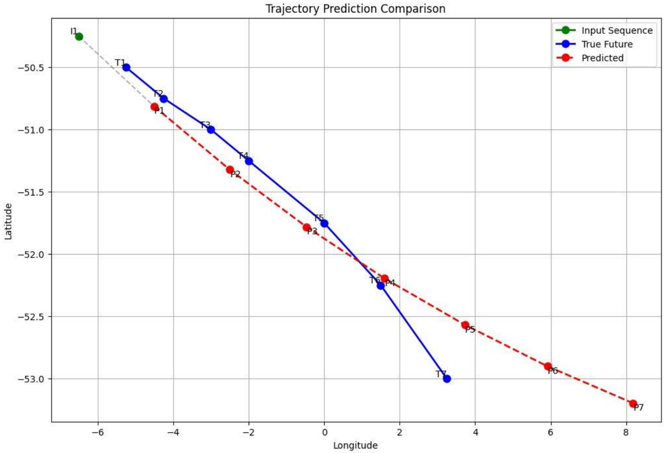

Figure shows the track by Transformer based model

- ❏ Manually collected the dataset via EddyClicker
- ❏ Detected Polar lows with CNN-based model
- ❏ Using various ML models predicted the trajectory of a Polar low

Conclusion

The best approach for the classification of the polar lows - CNNs

The best approach for the trajectory prediction - Transformer-based models

Future work perspectives:

Conduction of the experiments on the more extended and bigger datasets with more refined models (CNN, transformers)

Identification between polar lows and other cyclones

Thx!

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