Multi-branch Spatio-Temporal Graph Neural Network For Efficient Ice Layer Thickness Prediction

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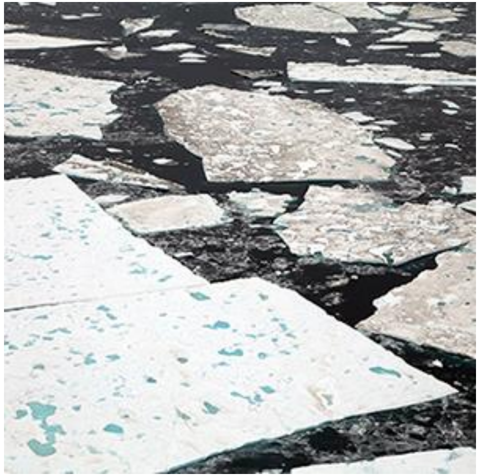
Motivation

- Global warming has caused serious damage to our environment.
- Accelerated loss of ice from Greenland and Antarctica
- Considerable influence on sea level rise and altering ocean currents
- Leading to the flooding of the coastal regions and putting millions of people around the world at risk

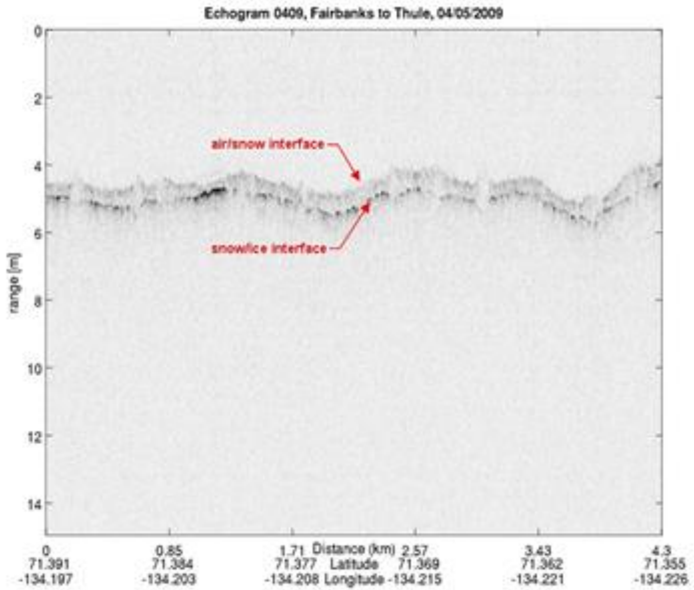


Motivation

- The Intergovernmental Panel on Climate Change estimates that the sea level could increase by 26–98cm by the end of this century.
- This large range in predicted SLR can be partially attributed to an incomplete understanding of **bed topography, snow accumulation, and ice dynamics**.
- Precise calculation of **ice thickness** is very important for sea level and flood monitoring.

Tracking the internal layers of ice sheet

- Tracking the internal layers of an ice sheet is important for calculating **surface mass balance**
- This helps in extrapolating **ice age** from subsurface measurements and inferring otherwise difficult-to-observe **ice dynamic** processes
- A precise understanding of the spatiotemporal variability of snow accumulation in the Greenland ice sheet is important to **reducing the uncertainties** in current climate model predictions and future **sea level rise**.

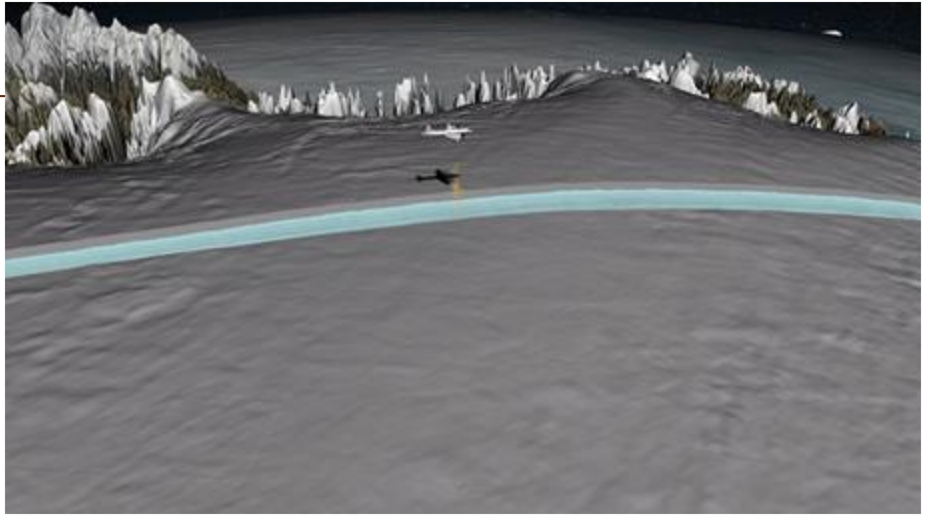


Traditional techniques

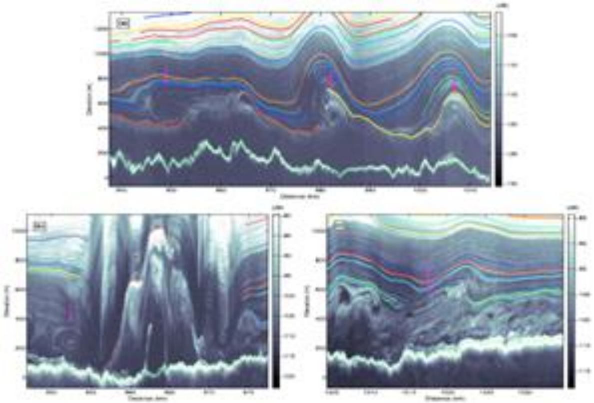
- Capturing ice layer thickness is difficult
- Generally done by gathering ice cores
  - Expensive
  - Hard to gather
  - Cover a small area
  - Limited in depth
  - Invasive

Airborne Radar

- Airborne radar has become a popular method of gathering thickness measurements
- Echograms are very noisy
- Ice layer borders are difficult to distinguish
- Tracking englacial ice layers is difficult because of the **large number of layers**, their **close proximity** to each other, and their common **discontinuities**.
- The number, thickness, and curvature of layers can vary across an ice sheet and are **not consistent**, unlike the bedrock which is present throughout

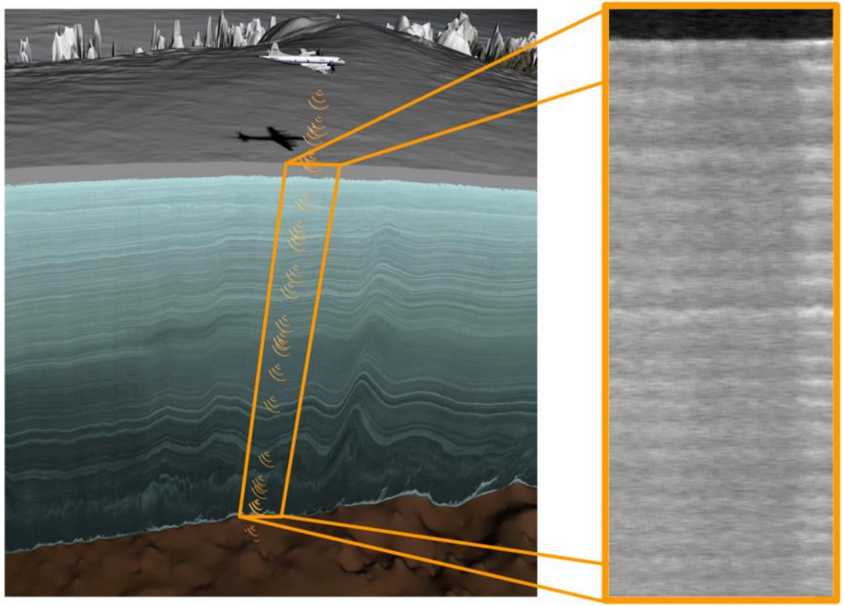


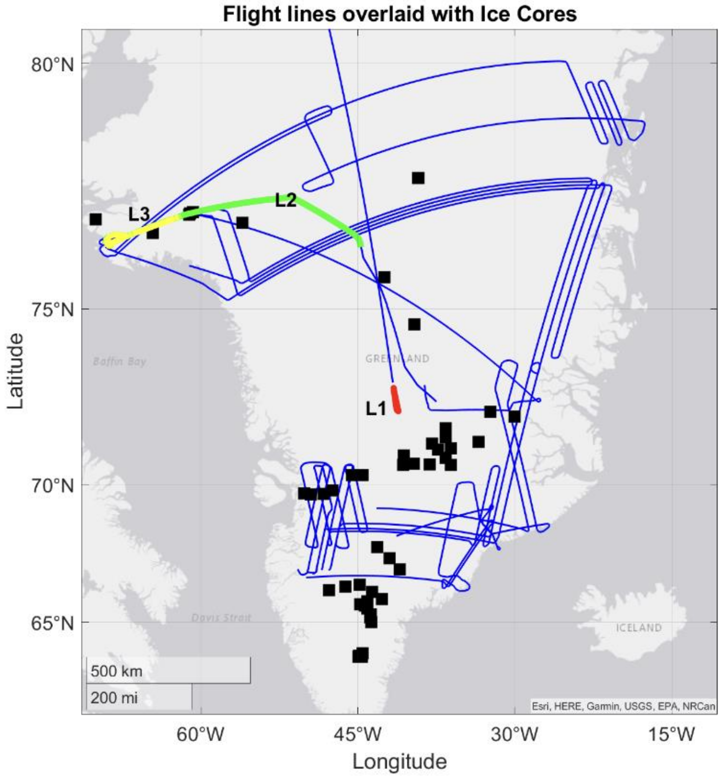
Starr, C. (2017). *Greenland Ice Sheet Stratigraphy*. NASA's Scientific Visualization Studio. Retrieved from https://svs.gsfc.nasa.gov/4249.



Snow Radar

	Snow Radar Parameters
Bandwidth	2-8 GHz
Pulse duration	250 μs
PRF	2 kHz
Transmit power	100 mW
Intermediate frequency range	62.5-125 MHz
Sampling frequency	125 MHz
Range resolution	$\sim$ 4 cm
Along-track footprint	14.5 m





Spatial plot of dataset flight lines and neighboring ice cores. Flight lines in Blue are the training data while those in Red (L1), Green (L2), and Yellow (L3) are the test data.

Previous works

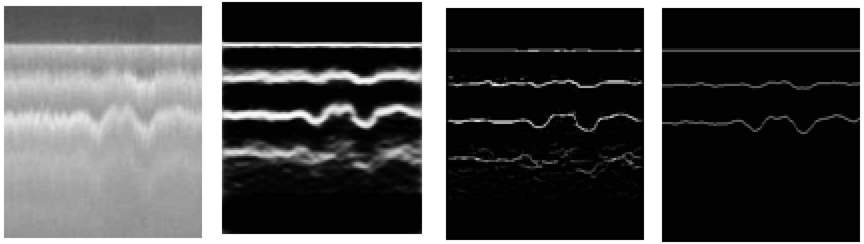
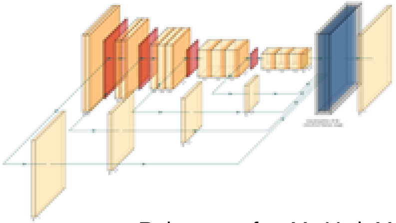
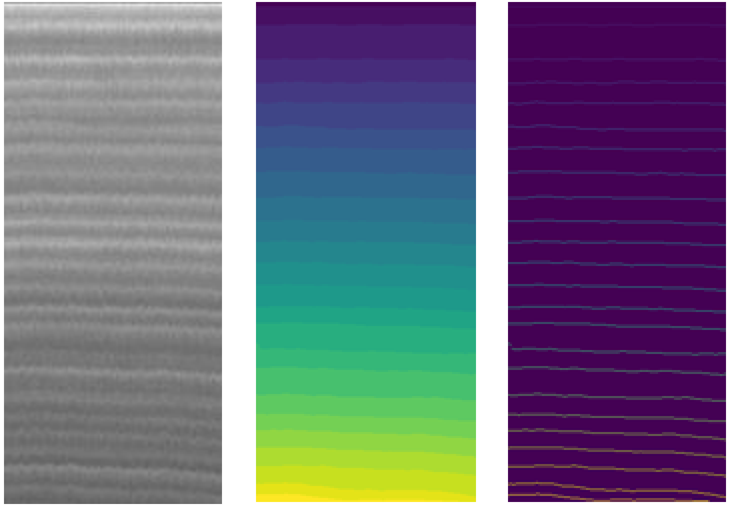


image result DL Mode nms post-process (non maximal suppression) ground truth get measures (OIS, ODS, F-measure)



Rahnemoonfar, M., Yari, M., Paden, J., Koenig, L., & Ibikunle, O. (2021). Deep multi-scale learning for automatic tracking of internal layers of ice in radar data. *Journal of Glaciology*, *67*(261), 39-48. doi:10.1017/jog.2020.80



Input Image Predicted Output Converted to Layers

GT Thickness	Predicted Thickness
22.57	21.4
38.36	40.46
28.29	27.13
24.04	23.91
28.71	29.77
24.61	23.54
28.5	28.54
29.03	29.18
27.78	28.01
24.59	24.33
25.84	25.23
26.23	26.25
25.88	25.31
20.62	20.08
32.55	30.41
18.86	21.98
31.28	31.27
23.36	23.42
19.31	19.13
19.05	20.41
22.22	21.35
25.02	23.18
13.3	11.62

Thickness Prediction

Varshney, D.; Rahnemoonfar, M.; Yari, M.; Paden, J.; Ibikunle, O.; Li, J. Deep Learning on Airborne Radar Echograms for Tracing Snow Accumulation Layers of the Greenland Ice Sheet. *Remote Sens.* **2021**, *13*, 2707. https://doi.org/10.3390/rs13142707

Previous works

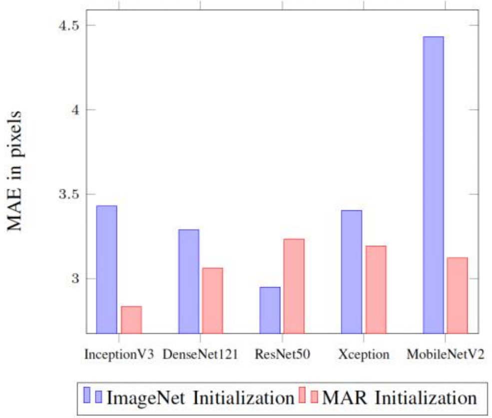
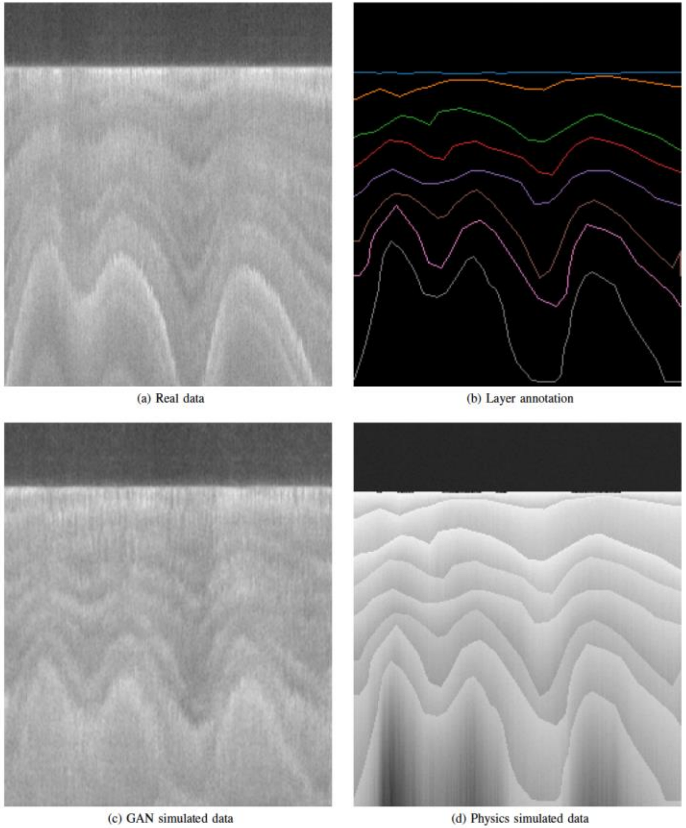


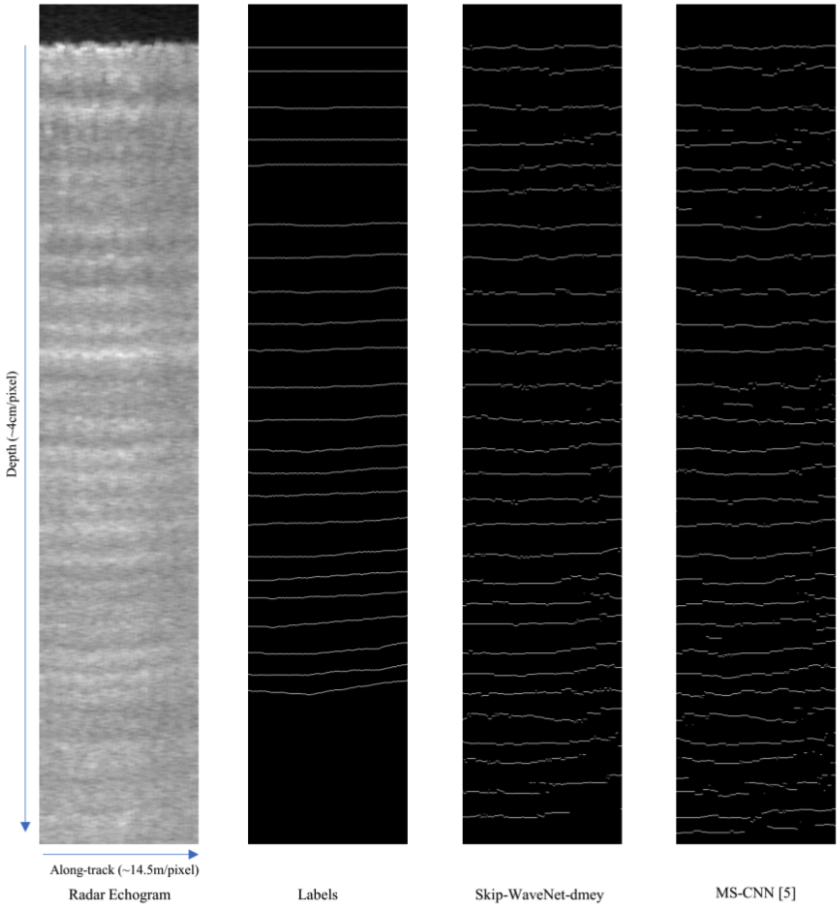
Fig. 3. Mean absolute error (MAE) of thickness estimation over the test set

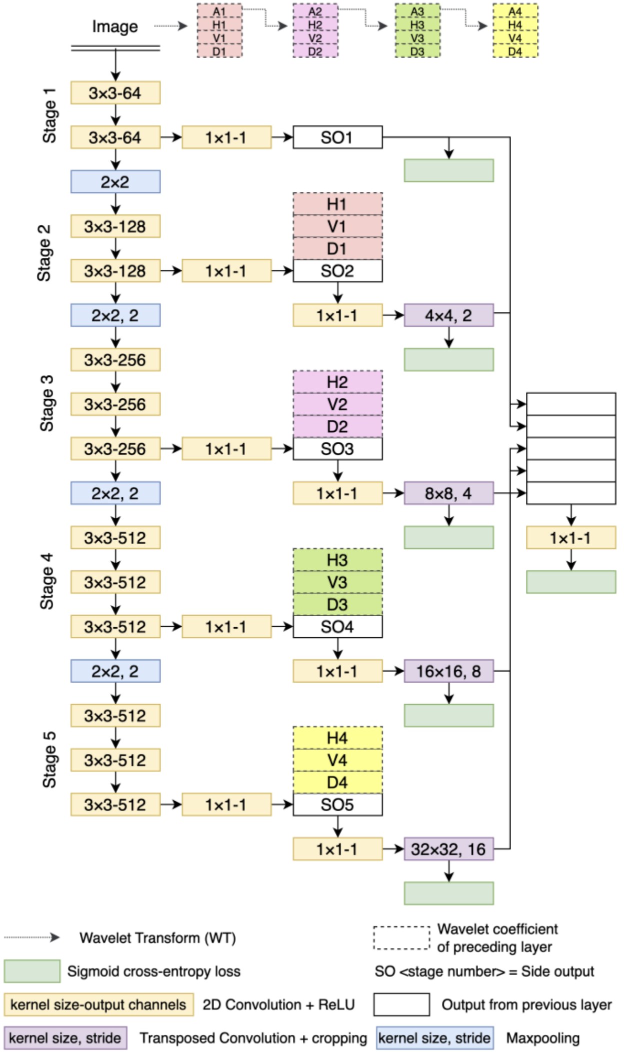
D. Varshney, O. Ibikunle, J. Paden and M. Rahnemoonfar, "**Learning Snow Layer Thickness Through Physics Defined Labels**," *IGARSS 2022*



Yari, M., Ibikunle, O*., Varshney, D.*, Paden, J., Rahnemoonfar, M., **Airborne Ice Penetrating Radar Data Simulation with Deep Learning and Physics-driven Methods**", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2021

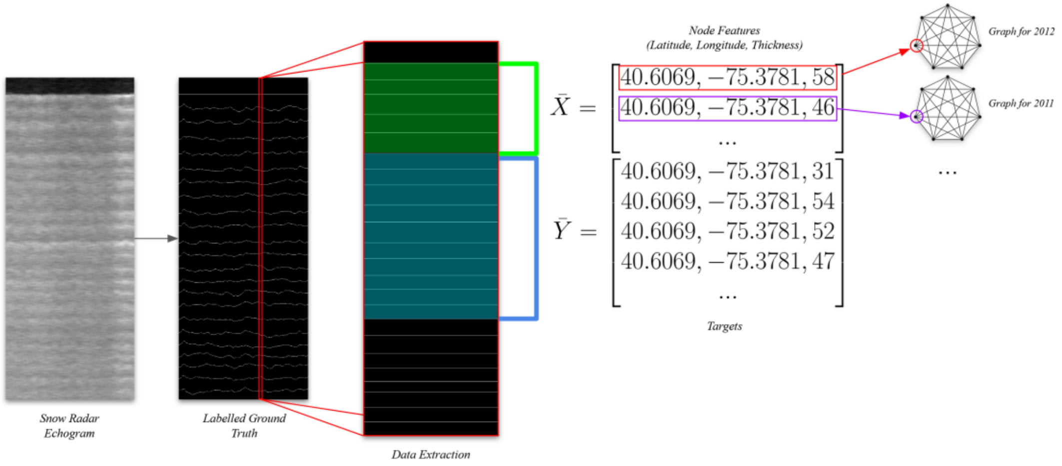
Previous works





Graph Convolutional Networks

- Is it possible to predict the thickness of deep ice layers given the thickness of shallow ice layers?
- Each echogram is converted to a series of temporal graphs
- Each ice layer becomes one graph
- Each column of pixels becomes one node in each graph

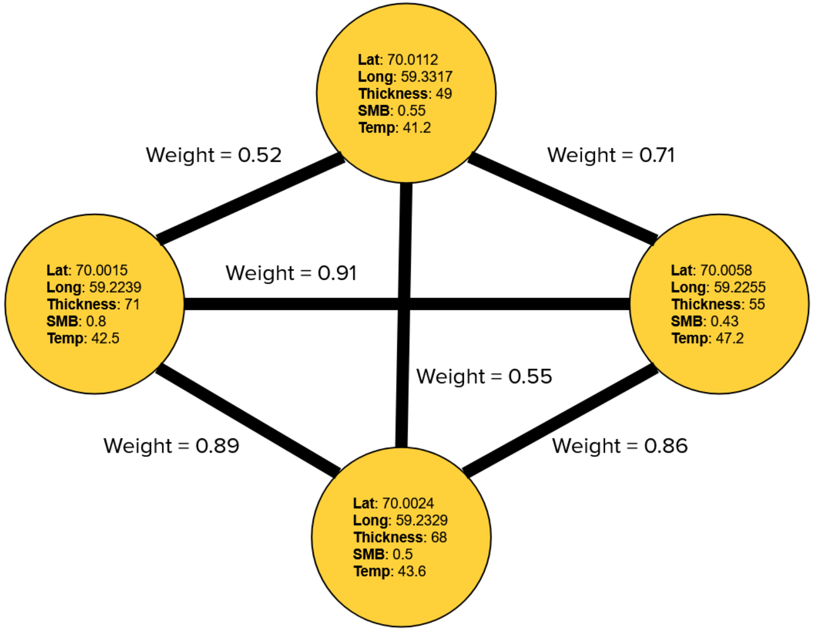


Each node always has three base features:

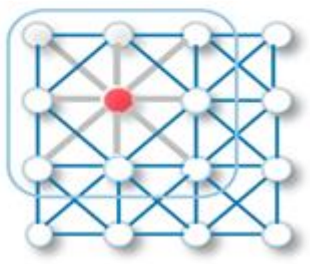
1. Latitude
2. Longitude
3. Ice layer thickness

Physical features from MAR

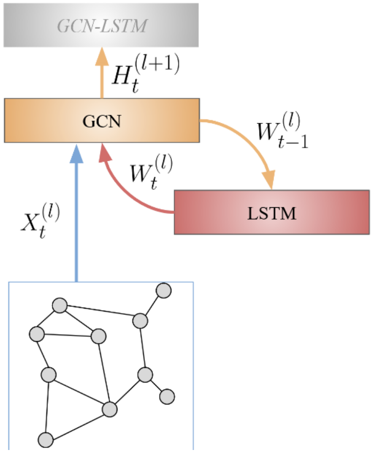
1. Snow mass balance
2. Surface temperature
3. Meltwater refreezing
4. Height change due to melt
5. Amount of snowpack

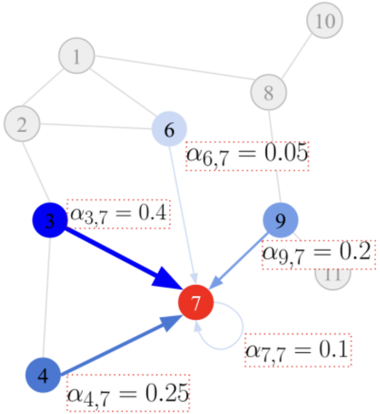


Graph Convolutional neural networks



EvolveGCNO





B. Zalatan and M. Rahnemoonfar, "Recurrent Graph Convolutional Networks for Spatiotemporal Prediction of Snow Accumulation Using Airborne Radar," *2023 IEEE Radar Conference (RadarConf23)*, 2023

B. Zalatan and M. Rahnemoonfar, "Prediction of deep ice layer thickness using adaptive recurrent graph neural networks," *2023 IEEE Conference on Image Processing (ICIP23)*, 2023

B. Zalatan and M. Rahnemoonfar, "Prediction of Annual Snow Accumulation using a Recurrent Graph Convolutional Approach," IGARSS *2023*

M. Rahnemoonfar and B. Zalatan, "Physics-informed Machine Learning for Deep Ice Layer Tracing in SAR images," *IGARSS 2024*

Fused Spatio-Temporal Graph Neural Network

Related work: Represent ice layer as **graphs** and use a **fused spatio-temporal graph neural network** that plugs Graph Convolution Network into LSTM

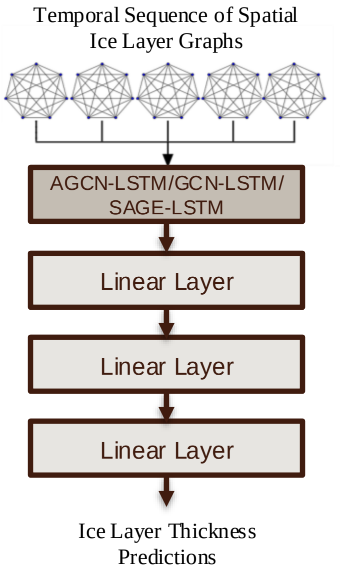
(a) Fully-Connected LSTM

$$
\begin{aligned}
i &= \sigma(W_{xi} * x_t + W_{hi} * h_{t-1} + w_{ci} \odot c_{t-1} + b_i),\\
f &= \sigma(W_{xf} * x_t + W_{hf} * h_{t-1} + w_{cf} \odot c_{t-1} + b_f),\\
c_t &= f_t \odot c_{t-1} + i_t \odot \tanh(W_{xc} * x_t + W_{hc} * h_{t-1} + b_c),\\
o &= \sigma(W_{xo} * x_t + W_{ho} * h_{t-1} + w_{co} \odot c_t + b_o),\\
h_t &= o \odot \tanh(c_t),
\end{aligned}
$$

Replace Dot Product with graph convolution

Graph convolution LSTM

$$
\begin{aligned}
i &= \sigma(W_{xi} *_{\mathcal{G}} x_t + W_{hi} *_{\mathcal{G}} h_{t-1} + w_{ci} \odot c_{t-1} + b_i),\\
f &= \sigma(W_{xf} *_{\mathcal{G}} x_t + W_{hf} *_{\mathcal{G}} h_{t-1} + w_{cf} \odot c_{t-1} + b_f),\\
c_t &= f_t \odot c_{t-1} + i_t \odot \tanh(W_{xc} *_{\mathcal{G}} x_t + W_{hc} *_{\mathcal{G}} h_{t-1} + b_c),\\
o &= \sigma(W_{xo} *_{\mathcal{G}} x_t + W_{ho} *_{\mathcal{G}} h_{t-1} + w_{co} \odot c_t + b_o),\\
h_t &= o \odot \tanh(c_t).
\end{aligned}
$$



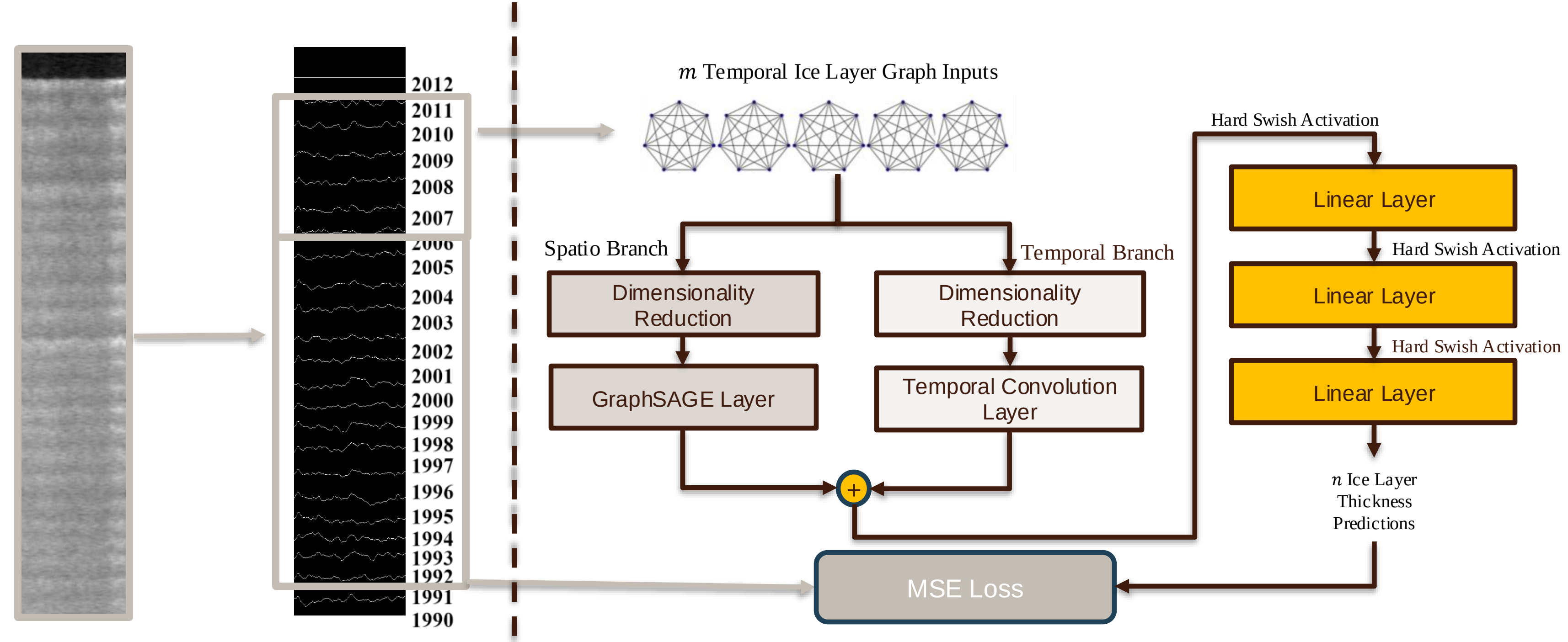
(b) Fused Spatio-Temporal Graph Neural Network

Figure: Diagram of previous fused spatio-temporal network

Multi-Branch Spatio-Temporal Graph Neural Network

- Motivation: Let each branch be more specialized and focus on one learning task!
- Goal: Improve both the **efficiency** and the **accuracy** of previous fused spatiotemporal graph neural network
- Contribution: We proposed **a universal multi-branch spatiotemporal graph neural network** that learns from the **upper** $\boldsymbol{m}$ **ice layers** and predicts the thickness for the **underlying** $\boldsymbol{n}$ **layers**

Multi-Branch Spatio-Temporal Graph Neural Network



(a) Radargram (b) Labeled images (c) Architecture of our proposed network

Dimensionality Reduction

Dimensionality Reduction: Remove irrelevant features

Spatio Branch: Aggregate to construct a compressed spatial graph and remove redundant features

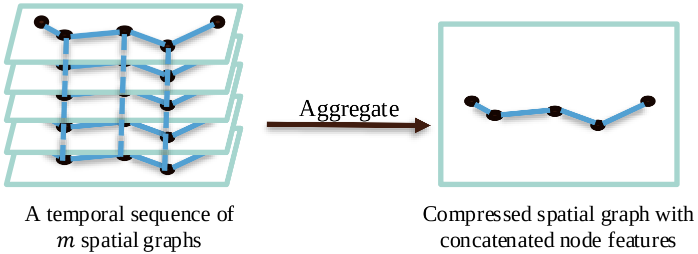


Figure: Dimension Reduction for spatio branch

Temporal Branch: Exclude the latitude and longitude from the initial node feature

GraphSAGE

GraphSAGE Inductive Framework: Sample and aggregation

For a certain node i and its node feature x_i, GraphSAGE will sample and aggregate its neighbor nodes' representation, defined as follows:

$\boldsymbol{x}_i' = \boldsymbol{W}_1 \boldsymbol{x}_i + \boldsymbol{W}_2 \cdot mean_{j \in N(i)} \boldsymbol{x}_j$

Where $\boldsymbol{x}_i'$ is the output of GraphSAGE,
$\boldsymbol{W}_1, \boldsymbol{W}_2$are the layer weights,
$N(i)$ is the sampled neighbor list of node i,
$\boldsymbol{x}_j$ is the node feature of neighbors and
mean is the aggregation function

Temporal Convolution

Gated linear unit with 2D convolution and skip connection

P, Q, R are calculated by a 2D convolution on the input node features $X' = ReLU(GLU(P, Q) + R)$

Where P, Q, R are achieved via three 2d convolution and $GLU(P, Q) = P \times \sigma(Q)$

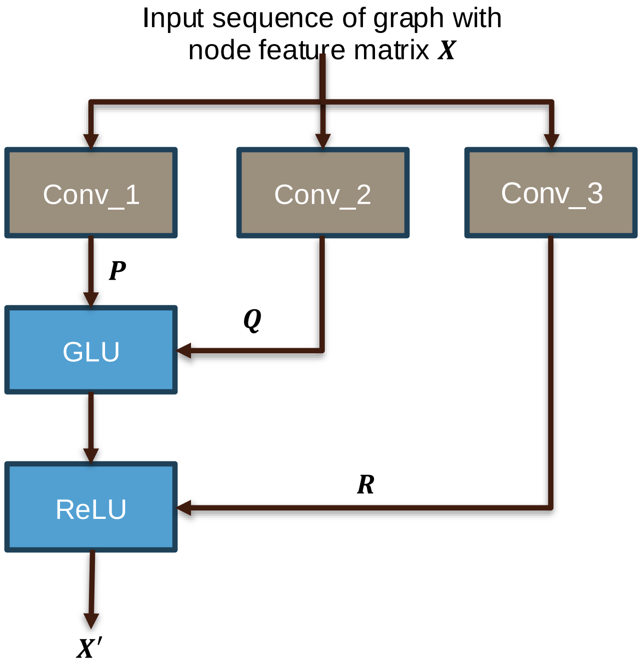


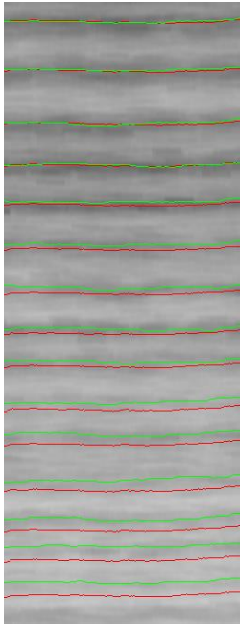
Figure: Diagram of Temporal Convolution Block

Overall Performance

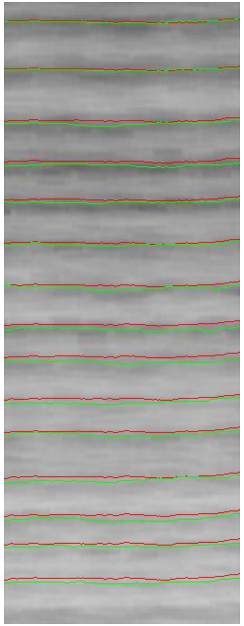
Table: Experiment results of GCN-LSTM, GraphSAGE-LSTM, and our proposed Multi-branch model. Results are reported as the mean and standard deviation of the RMSE on the test dataset over five individual trials. Train time is reported as the average train time over five individual trials

Model	RMSE	Training Time (Second)
GCN-LSTM	3.2106 ± 0.1188	7136
SAGE-LSTM	3.1949 ± 0.0332	4574
MB-STGNN	$\mathbf{3.1236 \pm 0.0548}$	**978**

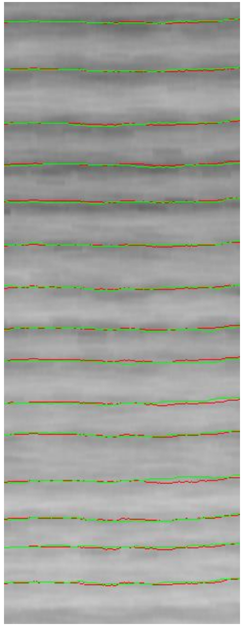
Qualitative Results



(a) GCN-LSTM



(b) SAGE-LSTM



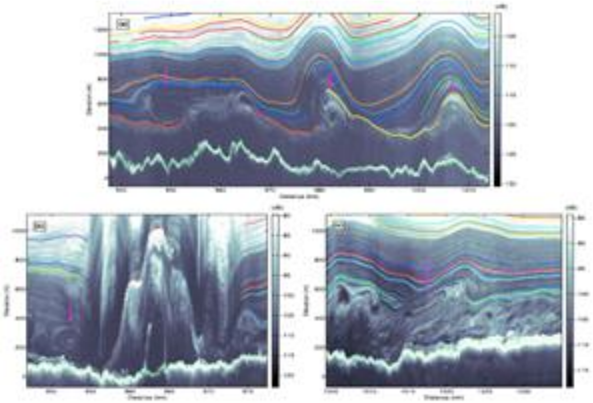
(c) Proposed
Multi-branch

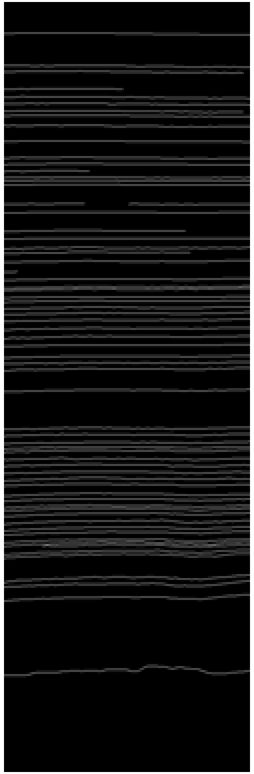
Figure: Qualitative results of model predictive. The green line is the ground truth and the red line is the model prediction.

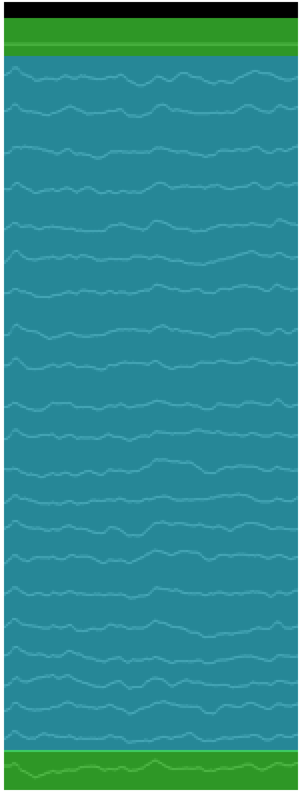
Summary

- Multi-branch spatial-temporal networks demonstrate superior performance over fused networks in terms of both accuracy and processing speed.

- More comprehensive analysis is required for deeper ice layers, incorporating data from various radar sensors and across different geographic regions







Thank You!