AI for Climate Change
Laboratory 1

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Project Theme: Monitoring and predictions in climate changes with effects on ice melting

Article 1: Predicting Ice Flow using Machine Learning

- **Dataset:**
  - **Name:** IceNet
  - **Source:** LANDSAT 8 satellite images
  - **Description:** Multi-spectral images with 7 bands (0.43m to 2.29m, covering visible, near-infrared, and shortwave light)
  - **Spatial Resolution:** 30 meters
  - **Temporal Coverage:** November 2015 – February 2017
  - **Total Images:** 10,675
  - **Frame Details:**Each image has 12 frames (128 × 128 pixels), with time intervals between 2 weeks to 9 months
  - **Availability:** Not explicitly mentioned
- **Algorithms Used:**
  - **Main Approach:** Stochastic Video Generation with Prior for Prediction
  - **Architecture:**
    - **Convolutional LSTM (Long Short-Term Memory)**: Used for temporal modeling
    - **Deep Convolutional GAN (Generative Adversarial Network)**: Used for image prediction
  - **Training Process:**
    - The prior network observes past frames to model a normal distribution
    - Uses KL divergence loss and L2 penalties for optimization
    - Latent space representation z is generated from previous subscenes
  - **Hyperparameters:**
    - Latent space: $z \in R^{128}$
    - 2 LSTM layers with 128 units each
    - Model conditions on past 8 subscenes for prediction
- **Metrics:**
  - **Correlation Index (CI):** Measures similarity between predicted and actual subscenes
  - **KL Divergence Loss:** Ensures that the learned distribution follows a normal distribution
  - **L2 Loss:** Penalizes differences between predicted and actual subscenes
  - **High-Pass Filter Performance:** Evaluates texture extraction accuracy for ice flow tracking
- **Results:**
  - **Successes:**
    - The ML model reproduced ice flow patterns with proper slopes accurately
    - Improved correlation between subscenes compared to high-pass filtering methods
    - Enhanced ability to track small textures with increased hidden space and batch size
  - **Challenges:**
    - High-pass filtering sometimes generated noisy signals, leading to incorrect correlations
    - Cloud cover occasionally affected the dataset, causing missing information
    - The balance between capturing small textures and large-scale ice movement was tricky

Article 2: [Machine Learning for Sea Ice Monitoring From Satellites]

- **Dataset:**
  - **Name:** Sentinel-1 Synthetic Aperture Radar (SAR) dataset
  - **Source:** Copernicus ESA (Sentinel-1 mission)
  - **Description:**
    - C-band SAR images for sea ice monitoring.
    - Dual-polarized (HH and HV) images.
    - High-resolution data (pixel spacing of 10×10 meters, geo-coded resolution of 20×22 meters).
  - **Temporal Coverage:** April - December 2018 (images taken on April 17, June 16, August 9, October 10, and December 1).
  - **Geographic Focus:** Belgica Bank, Greenland.
  - **Availability:** Publicly accessible through the Copernicus Open Access Hub.
- **Algorithms Used:**
  - **Active Learning with Support Vector Machine (SVM)**
    - Used for semantic annotation and classification.
    - Extracts statistical descriptors from image patches.
  - **Variational Autoencoder (VAE)**
    - Used for representation learning of SAR images.
    - Encodes image patches into a latent space.
  - **k-Nearest Neighbors (k-NN)**
    - Used for classification and change detection.
    - Weighted k-NN with Euclidean distance and k=9k = 9k=9.
  - **Feature Extraction Techniques**
    - Gabor Filters: Extracts a 60-dimensional feature vector.
    - Weber Local Descriptors: Generates a 144-dimensional feature vector.
  - **Optimization**
    - Trained using the ADAM optimizer with a stopping criterion at a loss threshold of 0.359.
- **Metrics:**
  - **Precision**
  - **Recall**
  - **F1-score**
  - **Accuracy**
  - **Change Level Metric:** Measures ice changes by comparing the absolute differences in semantic category labels between images.
- **Results:**
  - **Classification Performance (averaged over all eight ice categories):**
    - k-NN (April 17th, 2018): 89% accuracy.
    - SVM (April 17th, 2018): 88% accuracy.
    - k-NN (June 16th, 2018): 88% accuracy.
    - SVM (June 16th, 2018): 82% accuracy.
  - **Change Detection Results**
    - Quantified changes in ice cover using labeled category shifts.
    - Generated semantic maps showing transitions in ice types.
    - Detected seasonal ice transitions (e.g., first-year ice turning into young ice, floating ice changing into water bodies).