ConvSNow: A tailored Conv-LSTM architecture for weather nowcasting based on satellite imagery

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WeADL 2024 Workshop

The workshop is organized by the Machine Learning research group

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Contents

Nowcasting - traditional methods and key challenges

- Short-term weather forecast (typically less than six hours)
- Vital for emergency alerts and timely actions
- Essential for meteorology, aviation, agriculture, construction, etc

Key challenges

- Predicting severe convective events
- Handling large datasets from satellites, radars, and ground stations

Nowcasting - traditional methods employed

- Extrapolation of radar and satellite data
- Numerical Weather Prediction (NWP):
  - Uses mathematical models of the atmosphere and oceans to predict weather based on current weather conditions
  - Highly detailed but computationally intensive, which can limit its practicality for short-term nowcasting

- Persistence-based nowcasting:
  - Simple and quick but fails to predict sudden weather changes

- Probabilistic and stochastic approaches:
  - Incorporates randomness and can model the uncertainty in weather predictions.
  - Provides a range of possible outcomes but can be less precise for specific predictions

Deep Learning in nowcasting

Why DL is important in nowcasting:

- Handles large volumes of data efficiently
- Capable of learning complex patterns in weather data
- Provides more accurate and timely predictions compared to traditional methods

Severe weather prediction:

- Focus on detecting and predicting severe weather phenomena like thunderstorms, hail, and tornadoes
- Use of RGB composites from satellite data to identify and track storm development

DL challenges:

- Ensuring models generalize well to different geographic regions and weather conditions
- Need for diverse training datasets to improve model robustness

ConvSNow model overview

- Combines the strengths of CNNs and LSTMs to handle both spatial and temporal data
- Processes sequences of satellite images to predict future atmospheric states
- Trained to predict the satellite frame S_{t+1} from a series of k frames at times $(t-k+1, t-k+2, \ldots, t)$
- The network is trained using a set of training samples in the form $(\{S_{t-k+1}, S_{t-k+2}, \ldots, S_t\}, \{S_{t-k+2}, S_{t-k+3}, \ldots, S_{t+1}\})$, where $S_i \in D$, $i = t-k+1, t-k+2, \ldots, t+1$, and $k = 4$
- ConvSNow model is capable to provide real-time nowcasting predictions based on Meteosat-11 RGB and channels

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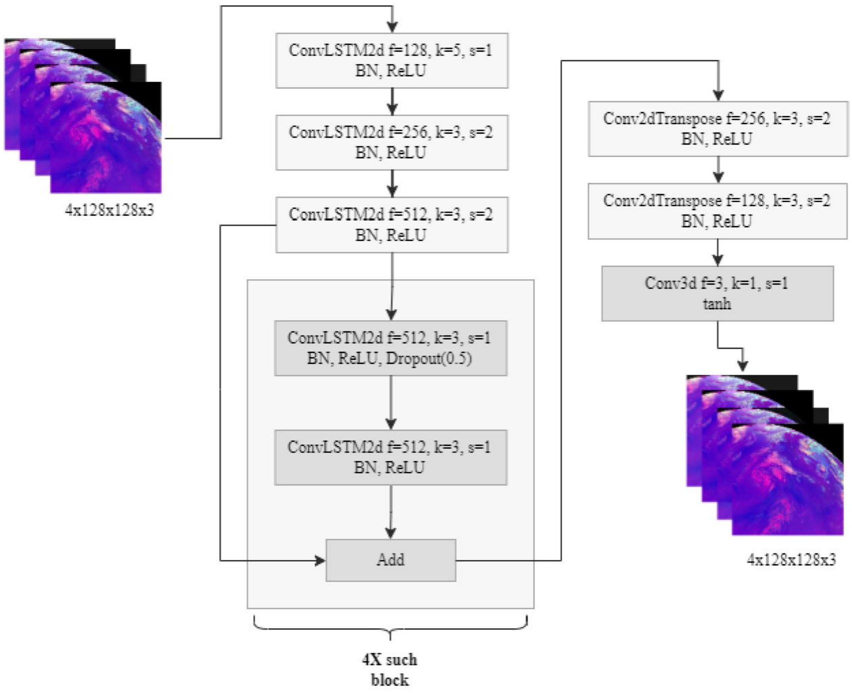
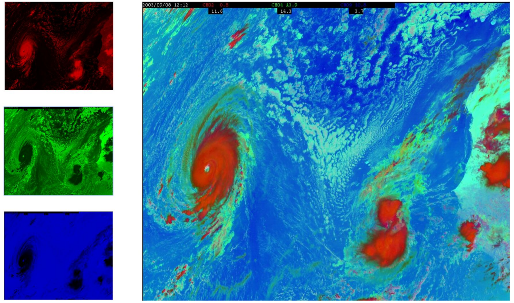
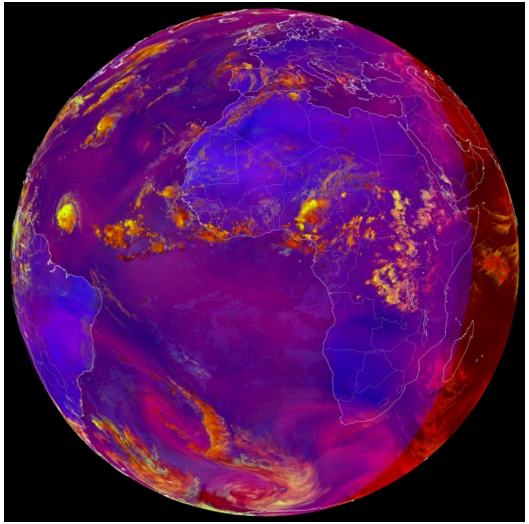
ConvSNow model architecture

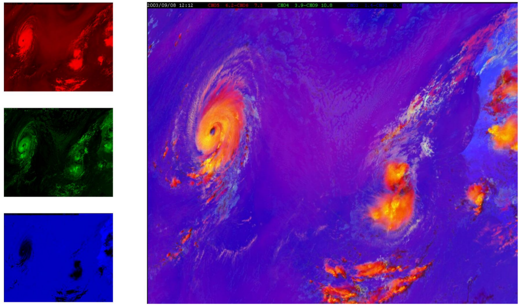


Meteorological satellites in nowcasting

- Cover large areas, providing extensive data for meteorological analysis
- Two main types: Geostationary and Polar-Orbiting satellites
- **Meteosat Second Generation** (**MSG**) Satellites - positioned in geostationary orbit, 35,786 km above the Equator, continuously monitoring the same area, providing 5 and 15 minutes updates







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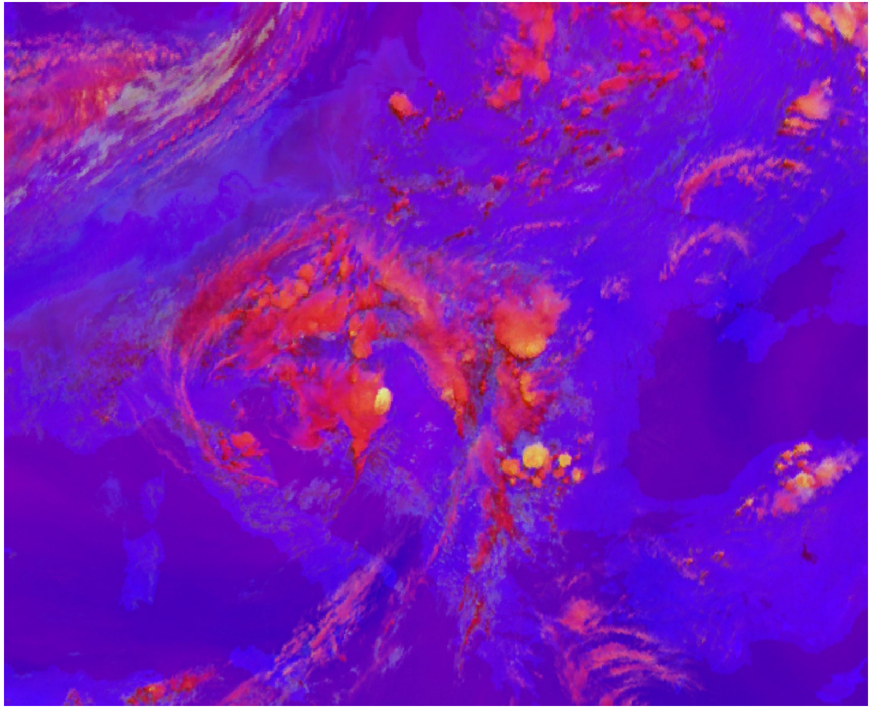
Data and methodology

- satellite imagery from EUMETSAT's Meteosat-11 satellite
- data collected over June 2021
- total of 2867 satellite frames used
- 80% of data used for training the model
- 20% reserved for testing and validation
- images arranged in sequences of k frames
- each sequence represents a series of images taken at consecutive time intervals
- series of k frames observed within the same geographical location
- example: frames at times (t-3, t-2, t-1, t) used to predict the frame at time (t+1)



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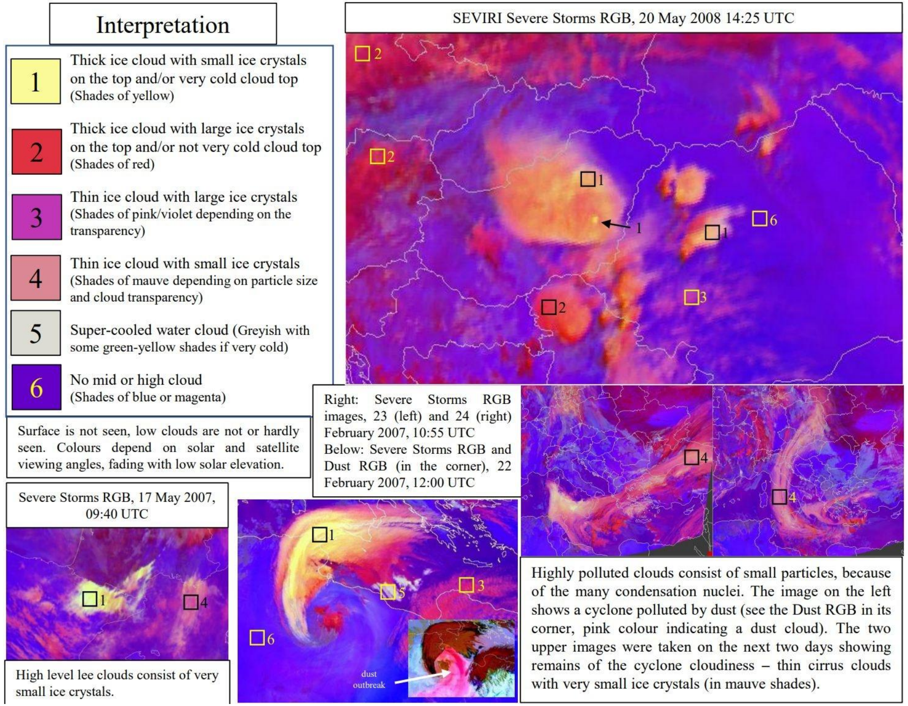
Data and methodology



Model training and architecture

- the model was trained for 40 epochs in batches of 2, and utilizing the Adam optimizer where the learning rate was adjusted by a factor of 0.5 each time the model was in a stable state for 7 epochs, the initial value being set to 0.001
- L1 regularization in all ConvLSTM layers was used for avoiding overfitting and improving the performance time
- after the first three ConvLSTM layers, Dropout Layers were added to minimize once more the risk of data overfitting by setting the input units' values to zero at a frequency of 0.5,
- All model's weights in each layer were randomly initialized using a normal distribution with mean 0 and standard deviation 0.02

Evaluation

To assess the performance of the ConvSNow model, three primary evaluation metrics were employed: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Normalized Mean Absolute Error (NMAE). These metrics provide a comprehensive view of the model's accuracy and precision in predicting weather patterns based on satellite imagery.

Model Performance The ConvSNow model was evaluated on a test set comprising 20% of the data (574 frames from the month of June 2021). The following results were obtained:

- **MAE**: 0.0169
- **MSE**: 0.0012
- **NMAE**: 1.6%

Evaluation

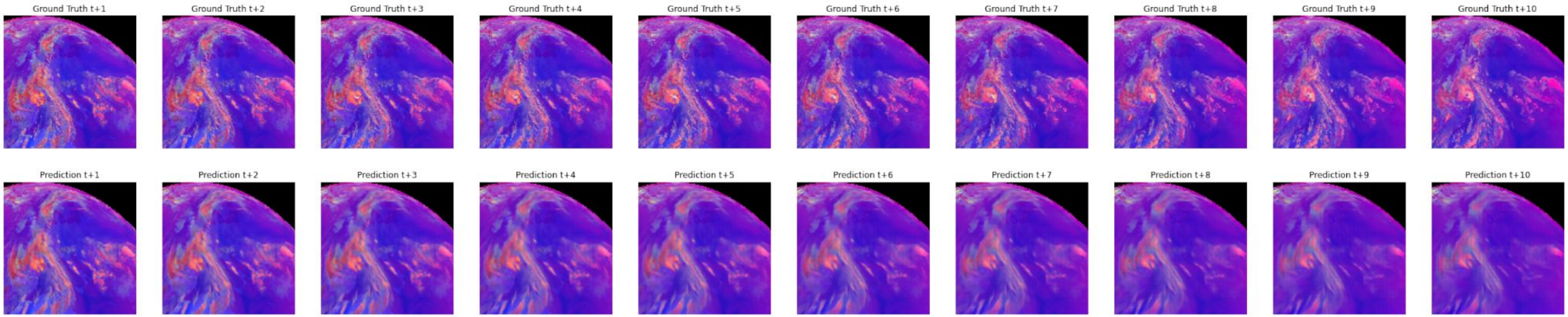
Comparison with Baseline Models The performance of the ConvSNow model was compared against three baseline models: CNN, U-Net, and Pix2Pix GAN. The results demonstrated that ConvSNow significantly outperformed these baselines in terms of MAE, MSE, and NMAE:

- **Baseline CNN**:
  - MAE: 0.0295
  - NMAE: 2.794%
  - MSE: 0.0029
- **Baseline U-Net**:
  - MAE: 0.0251
  - NMAE: 2.38%
  - MSE: 0.0022
- **Baseline Pix2Pix**:
  - MAE: 0.0305
  - NMAE: 2.39%
  - MSE: 0.0035

Relative Improvement ConvSNow achieved a relative improvement in NMAE of more than 30% compared to the baseline models:

Model	MAE	$NMAE$	MSE	Training (epochs/iterations)
$ConvSNow$	**0.0169**	**0.0160**	**0.0012**	40 epochs
Baseline CNN	0.0295	0.02794	0.0029	32 epochs
Baseline U-Net	0.0251	0.0238	0.0022	40 epochs
Baseline Pix2Pix	0.0305	0.0239	0.0035	40000 iterations
Relative improvement of $ConvSNow$	**42.7%**	**32.7%**	**44.6%**	

Results and evaluation



Samples for real output (upper row) and predicted images (second row), total of 150 min lead time

Results and evaluation

- From a meteorological point of view, the analysis of time series prediction of Convection RGB Composite made by the ConvS Now are satisfying
- The model demonstrates reasonable accuracy in predicting the spatial and pixel values, particularly for the first hour, which is a common time span for thunderstorms severe weather warnings issued by meteorological offices
- Some degree of blurriness is noticeable from the first time steps, as expected in deep learning models
- As the anticipation horizon increases, the model tends to underestimate pixel values, which can be partially attributed to the difficulty of predicting the initiation of new convective cells

Conclusions and future improvements

- the proposed model it outperformed other three baseline approaches considered for comparison
- In terms of the NMAE evaluation metric, ConvsNow obtained a relative improvement of more than 30% compared to the other baseline approaches in capturing the spatio-temporal features
- we plan to extend the data set used for training and evaluation the ConvS Now model and to conduct an extensive comparison to other baseline models, in order to better assess the model's performance
- design a DL model trained on both radar and satellite data to test if the performance of the prediction may be enhanced by adding multiple data sources
- spatial area of interest could be reduced from a continental to a national or regional level, adjusted to the various requirements from operational nowcasting