Precipitation Nowcasting Using Deep Learning

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Abstract— Precipitation nowcasting for short-term storm forecasting (0–6 hours) is essential for timely severe weather warnings. Traditional methods such as numerical weather prediction (NWP) and radar extrapolation, often lack accuracy at short scales and are computationally intensive. Recent deep learning models, such as ConvLSTM and TrajGRU have offered promising advances by capturing complex spatiotemporal dynamics. This paper aims to evaluate these models on satellite data, addressing the limitation posed radar's limited global coverage, while focusing on the region of Sindh, Pakistan — a region with minimal meteorological infrastructure. Thus, by contributing towards the improvement of global nowcasting capabilities this work addresses critical forecasting needs heightened by climate change.

What is Precipitation Nowcasting?

It is the short-term (0–6 hours) forecasting of storm systems and is critical for timely severe weather warning, agriculture, and otherwise.

What it is the Challenge around it?

Traditional methods (Numerical Weather Prediction and Optical flow on radar/satellite data) lack accuracy at short scales and are computationally intensive

Our Approach

Using sequential deep learning models (ConvLSTM[1], TrajGRU[2]) for improved nowcasting using satellite data

Existing Works

1. Largely limited to radar data – has very limited geo-spatial extent
2. Performance tested only for nowcasting in specific regions
3. Tested with limited spatial and temporal resolution (30 min) satellite products (or datasets).

Our Work

- Testing performance on a new region: Sindh, Pakistan—a region with minimal meteorological infrastructure but strong monsoonal influence. See Fig.1
- Global Relevance: utilization of satellite-based data to overcome radar's limited global coverage.
- Improved prediction quality by using data with higher spatial (4km x 4km) and temporal resolution (30 min). Has not been used in existing literature thus far.

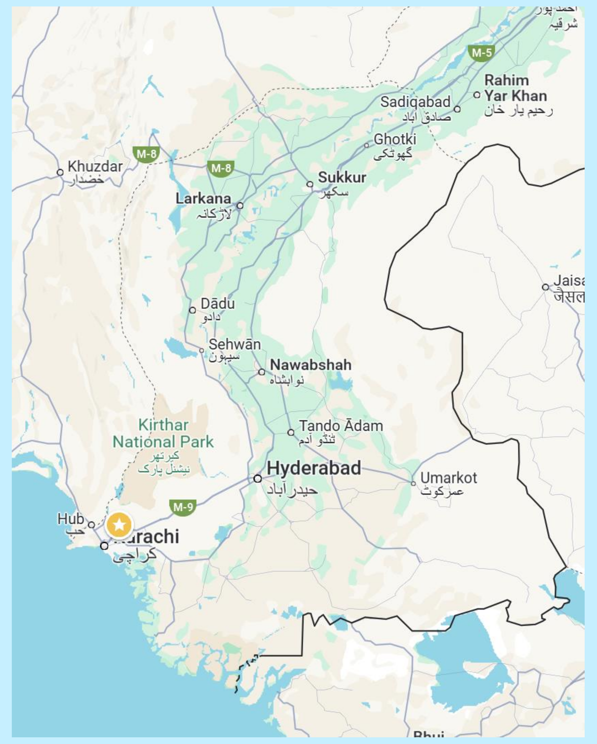

Fig. 1 Region of Interest

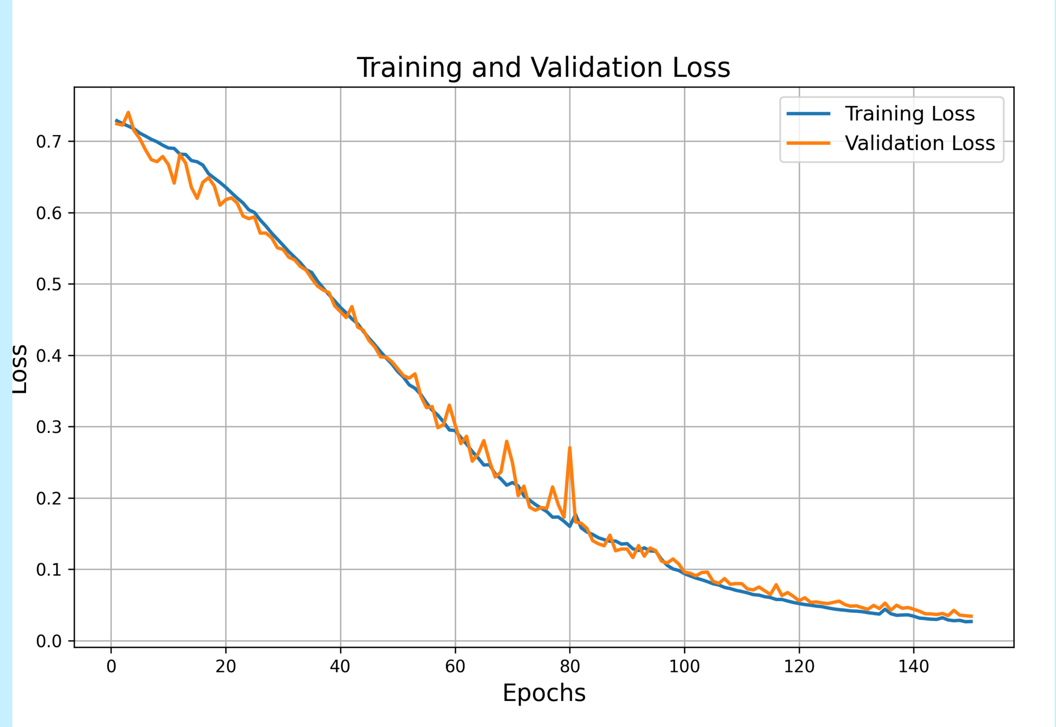

Fig. 2 Training and Validation Loss for ConvLSTM

Methodology

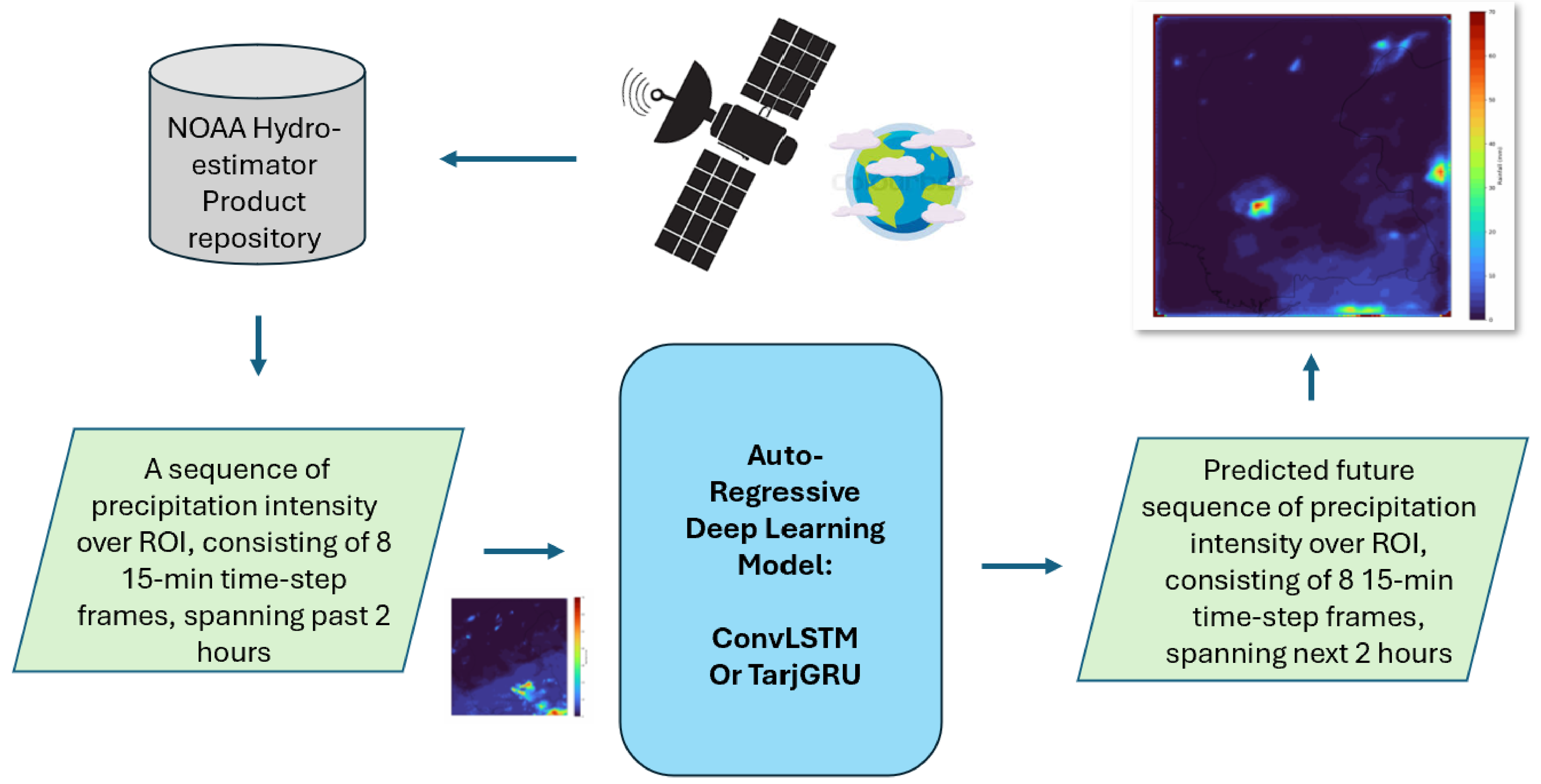

Fig.3. Methodology Outline

Result

- Dataset: spans Monsoon season (July – September) from 2019 to 2024 and days that have > 25mm precipitation.
- Loss Function: SSIM (70%) + MSE (30%) to balance spatial prediction

Parameter	Value
Total Seq.	1560
Training Seq.	1092
Validation Seq.	312
Testing Seq.	156
Seq. Length	16
Frame Size (HxW)	153x135
Min Rain Intensity	0
Max Rain Intensity	100

TABLE I
Dataset Details

Parameter	Value
Epochs	150
Learning Rate	0.001
Optimizer	Adam
Loss Function	SSIM + MSE
Training Loss	0.0268
Validation Loss	0.0342
Testing Loss	0.0352
GPU Used	A100
Environment Used	Google Colab Pro

TABLE II
Performance Details

Some Cool Visualizations!

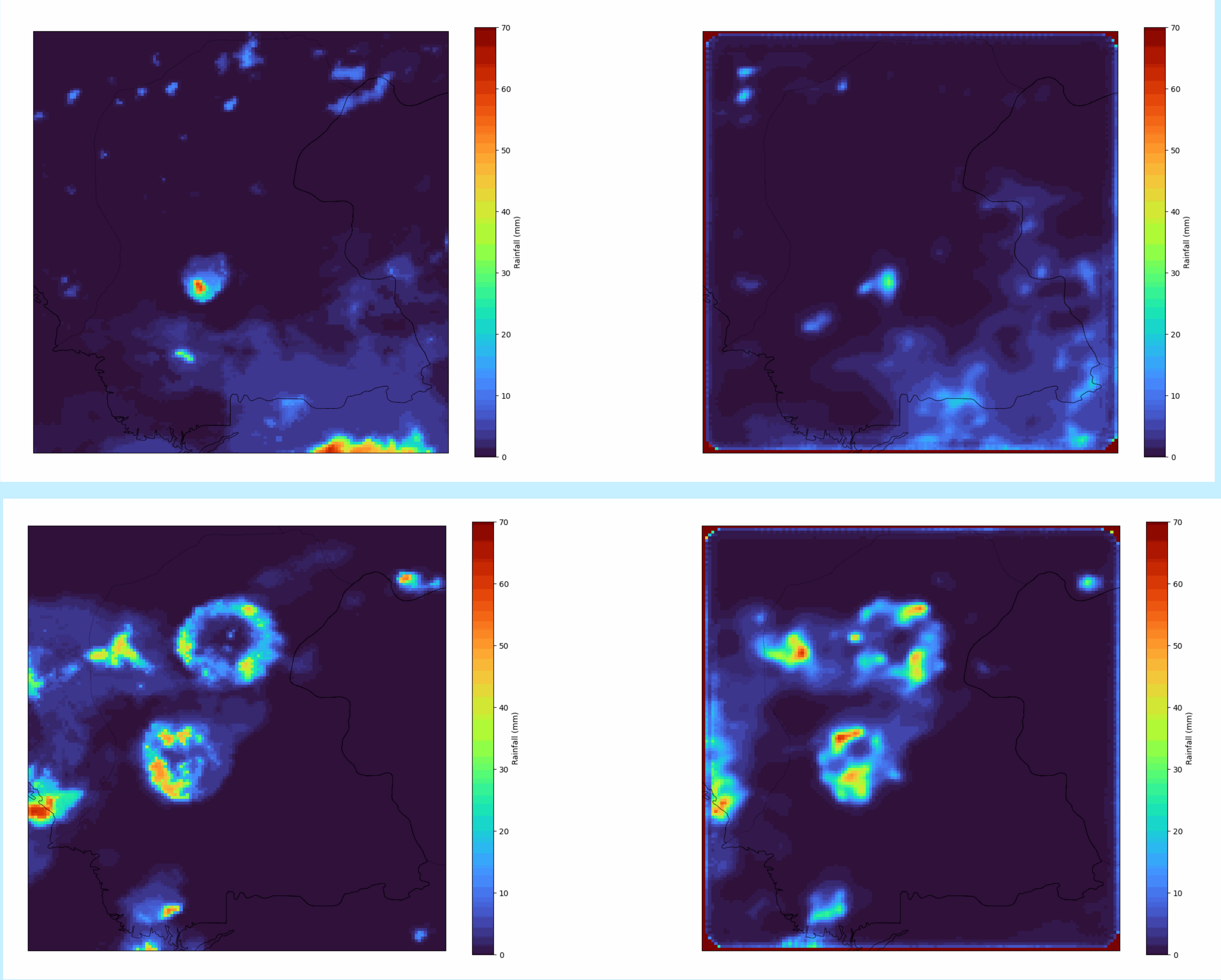

Fig. 4 Left (Target) Right (Prediction): The figure shows two prediction sequences generated by the trained model on test dataset samples

[1]Shi, X., Chen, Z., Wang, H., Yeung, D.Y., Wong, W., & Woo, W. (2015). Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting. Neural Information Processing Systems
[2]Shi, X., Gao, Z., Lausen, L., Wang, H., Yeung, D.Y., Wong, W., & Woo, W. (2017). Deep Learning for Precipitation Nowcasting: A Benchmark and A New Model. Neural Information Processing Systems.