Internship Details

- **Organisation** : Indian Space Research Organisation (ISRO)
- **Program** : SMART (Satellite Meteorology and OceAnography Research and Training)
- **Location** : Bopal, Ahmedabad, Gujarat
- **Internship Definition** : Extreme weather prediction using deep learning techniques on Indian subcontinent feature images.

Introduction

- **Sub Definition** : The goal of precipitation nowcasting is to predict the future rainfall intensity in a local region over a relatively short period of time.

- **Dataset** : INSAT3D

- **Time Interval** : 30 mins, 1hr, 2hr … 6hrs.

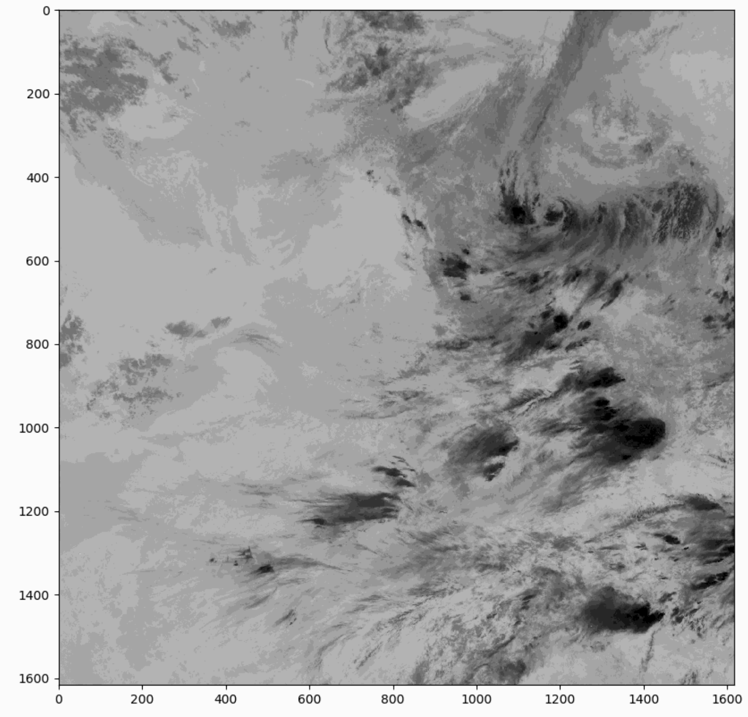
Datasets used in previous research

Filename	Title	Dataset Description	Additional points
		METAR windspeed data	57 stations -> stations
3.pdf	Deep Learning based Spatio-Temporal Forecasting	hourly data	
		Iowa data	compared with OSFS benchmark
		63 years daily data	idea of precursor image patterns leading to development of storms etc.
6.pdf [1]	Long Lead Prediction of Extreme Precipitation Cluster via ST-CNN	Temp, Zonal Wind, Meridional Wind, Geopotential Height at xxx hPa	
		Wunderground API data	
		15 years hourly data	
4.pdf	Seq. to Seq. Weather Forecasting with LSTM RNN	Temp, % humidity, Windspeed	
		CAM5.1 historical	Predict tropical cyclone, Weather Front, Atmospheric River
		ERA Interim reanalysis	
		20 century reanalysis	
7.pdf [1]	Application of Deep CNN for detecting extreme weather in climate datasets	NCEP-NCAR reanalysis	
		Nevada Climate Change Portal (online)	Prediction temperature SDAE vs FFNN
		hourly data (1 year)	
9.pdf	Forecasting Weather of Nevada: DL approach	Temp, % humidity, Precipitation, Windspeed	
12.pdf	Rainfall prediction using NN a survey	N/A	survey of rain prediction paper
		IGRA dataset	
8.pdf [1]	Hybrid model for weather forcasting	5 years of data (6, 12, 24 hrs)	focus on the models only
10.pdf	Weather forcasting using merged LSTM model	Wunderground API data	forcast ground usibility at airport
1.pdf [1]	Dynamic corv layer for sort-range weather prediction		

Yash Thesia(15bce126@nirmauni.ac.in) and Vidhey Oza(15bce130@nirmauni.ac.in), Nirma University, ISRO MOSDAC SMART program

Dataset Details

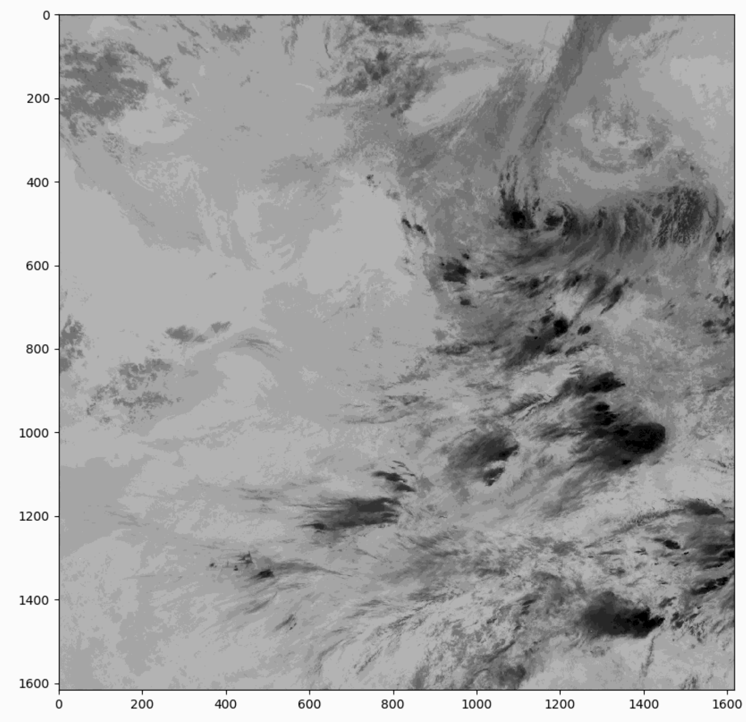
- INSAT 3D module
- 6 channel data
- 3 levels of processing
  - **L1**: Standard grey counts of different spectra (e.g., visible, shortwave IR, mid-wave IR)
  - **L2**: Geo-physical products (e.g., winds, rainfall, fog)
  - **L3**: Derived products (e.g., long-wave radiation, humidity)
- Preliminary work on L1C data
  - Asia Sector TIR1 Brightness Temperature



100 images of temperature level Indian subcontinent
Image interval: 30 mins/image

Dataset Preprocessing

- Satellite calibration errors
- Missing images
- Missing values within image



100 images of temperature level Indian subcontinent
Image interval: 30 mins/image

Preliminaries

- Forecasting of next frame; using this learning for extreme weather prediction
- Convolutional networks with consideration of sequence modelling
  - Conv3D (3D filters on multi-channel images)
  - ConvLSTM (proposed for the nowcasting problem)

ConvLSTM architecture

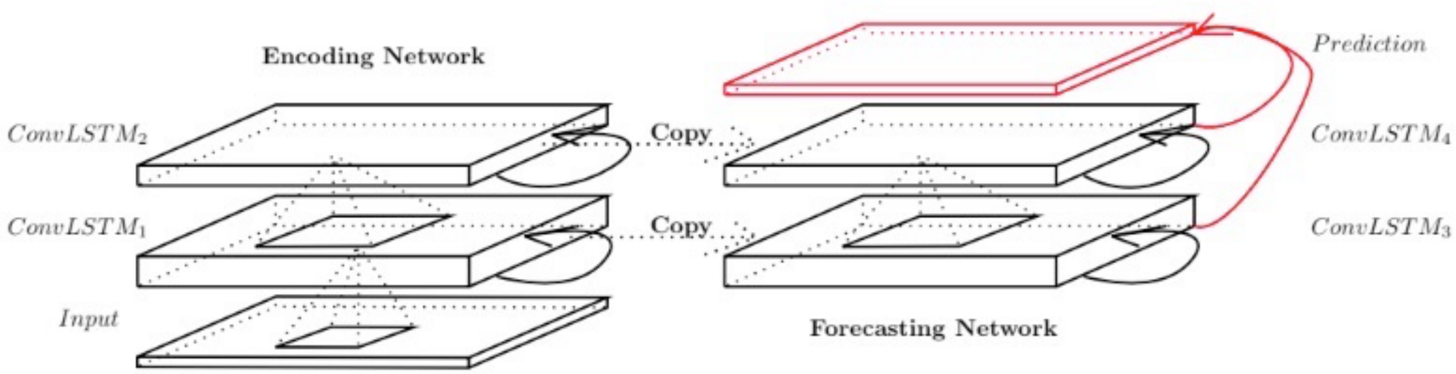


Fig. 4: Groundbreaking architecture of ConvLSTM node, as presented in [1].

Future Work and Subgoals

- Once preliminary efficacy of models and approaches established, move on to L2 or L3 products for more relevant data for extreme
- Different approaches for different extreme weather classes; to be discussed with domain experts on-site
  - Flood-like conditions due to extreme rainfall
  - Tropical Cyclones
  - Atmospheric Rivers
  - …

Extreme Weather Prediction using Deep Learning

Yash Thesia, Vidhey Oza
B. Tech. (CE) Semester 8
Institute of Technology
Nirma University

under Dr. Priyank Thakkar
Associate Professor

under Dr. Nitant Dube
Scientist/Engineer
Space Application Centre
ISRO

Yash Thesia: 15BCE126 , Vidhey Oza: 15BCE130

Project Definition

Objective: to predict next frames of different channels of data, followed by prediction of extreme weather event locations using these predicted frames.

DATASET DESCRIPTION

Standard Products (L1B) [INSAT-3D]

Sr. No.	Dataset Channel Name	Resolution (pixel distance)	Description
1	IMG_VIS	1km	Radiance for Visible Channel
2	IMG_SWIR	1km	Radiance for Shortwave Infrared Channel
3	IMG_TIR1	4km	Brightness Temperature for Thermal Infrared Channel 1
4	IMG_TIR2	4km	Brightness Temperature for Thermal Infrared Channel 2
5	IMG_MIR	4km	Brightness Temperature for Middlewave Channel
6	IMG_WV	8km	Brightness Temperature for Water Vapor Channel

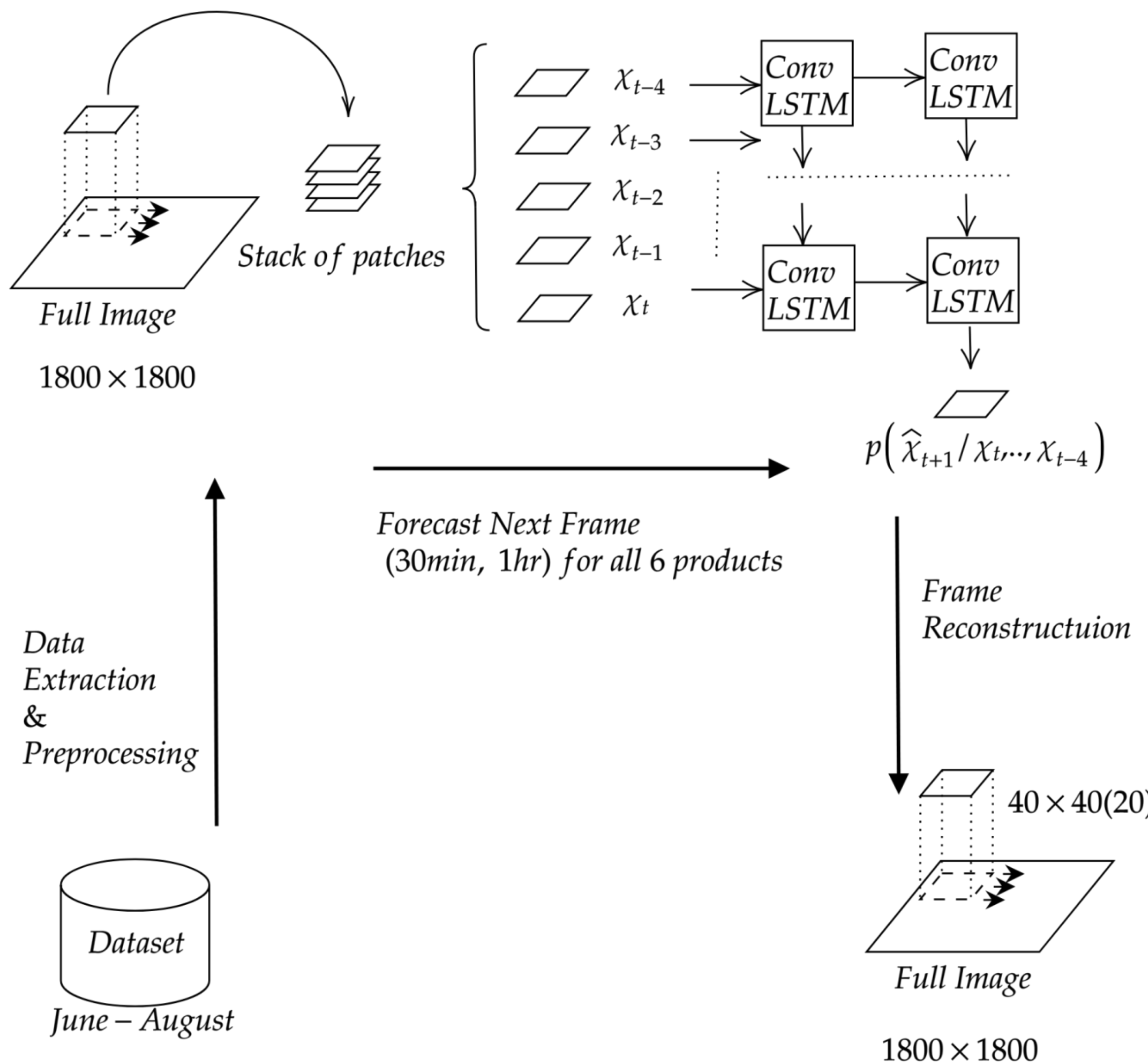
- **Temporal interval**: 30mins
- **Spatial area covered**: Indian Subcontinent (60° N to 60° S, 30° E to 130° E)
- **Total dataset size**: ~500GB per month

Derived Products

Sr. No.	Product Name	Resolution	Application	Dataset Period
1	Hydro Estimator Precipitation	8km	Used for extreme rainfall events	July to September
2	Land Surface Temperature	4km	Used for heatwave events	April to May
3	Sea Surface Temperature	4km	Used for correlation of heatwave events with SST variations	April to May
4	Fog	4km	Used for rare fog occurrences	November to December

IMPLEMENTATION

Implementation Details



Data Preprocessing

- Normalization
  - Min-Max scaling
- Noisy images
  - ~5% data noisy/corrupted
  - Skip these images by selecting continuous sliding window (>= 6)

Architecture

1. Convolutional LSTM
   – Proposed for precipitation nowcasting

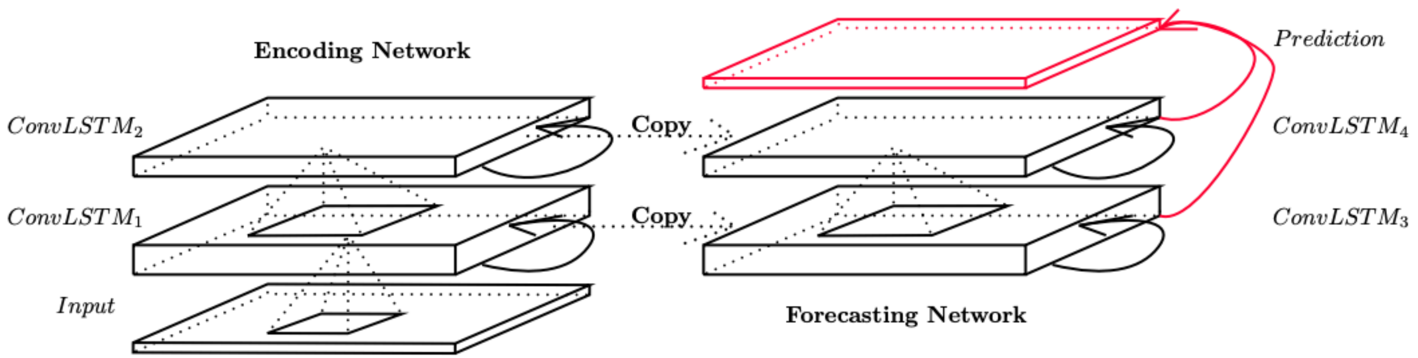


Figure 3: Encoding-forecasting ConvLSTM network for precipitation nowcasting

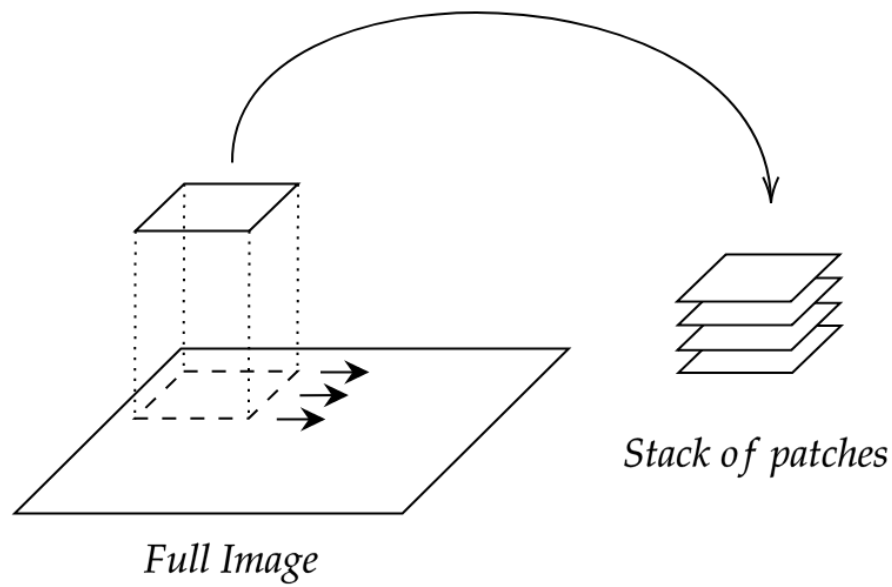
$$
\begin{aligned}
i_t &= \sigma(W_{xi} * \mathcal{X}_t + W_{hi} * \mathcal{H}_{t-1} + W_{ci} \circ \mathcal{C}_{t-1} + b_i) \\
f_t &= \sigma(W_{xf} * \mathcal{X}_t + W_{hf} * \mathcal{H}_{t-1} + W_{cf} \circ \mathcal{C}_{t-1} + b_f) \\
\mathcal{C}_t &= f_t \circ \mathcal{C}_{t-1} + i_t \circ \tanh(W_{xc} * \mathcal{X}_t + W_{hc} * \mathcal{H}_{t-1} + b_c) \\
o_t &= \sigma(W_{xo} * \mathcal{X}_t + W_{ho} * \mathcal{H}_{t-1} + W_{co} \circ \mathcal{C}_t + b_o) \\
\mathcal{H}_t &= o_t \circ \tanh(\mathcal{C}_t)
\end{aligned}
$$

Memory Utilisation

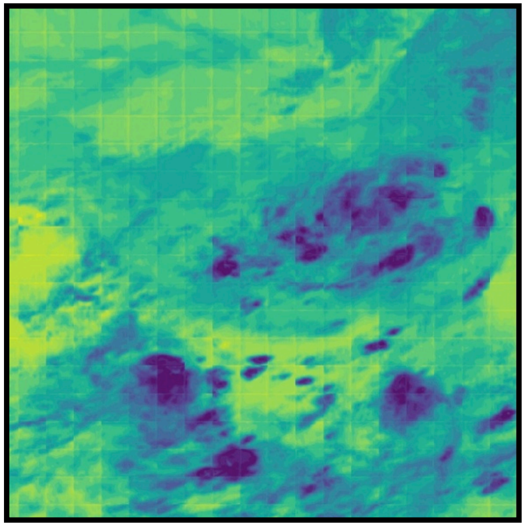
GPU(NVIDIA P600) VRAM	2GB
Next Frame Prediction Model (Convolutional LSTM)	3,35,137 parameters ~ 1.34GB
Remaining Memory	660 MB
Input tuple size (5 images input, 1 image output; size 1800x1800)	**19.6GB**
Max tuple size which we can fit into memory	1 tuple of 128x128 OR 4 tuple of 64x64

Solution

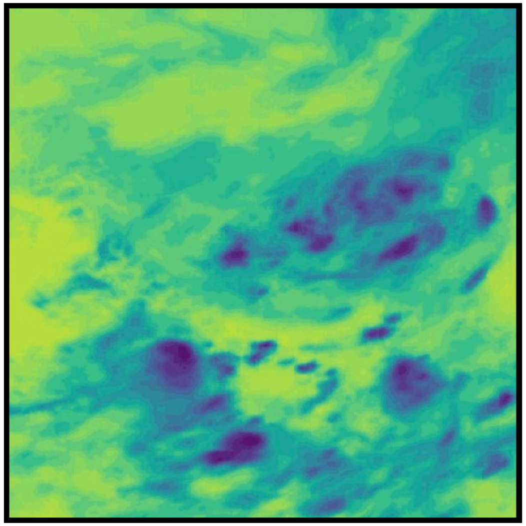
- **Patch generation using data augmentation**
  - Split 1800x1800 image into patches of 40x40
- **Problem with image reconstruction**
  - Square grid noise
- **Solve it by generating overlapping patches**
  - 40x40 patches with overlapping stride of 20



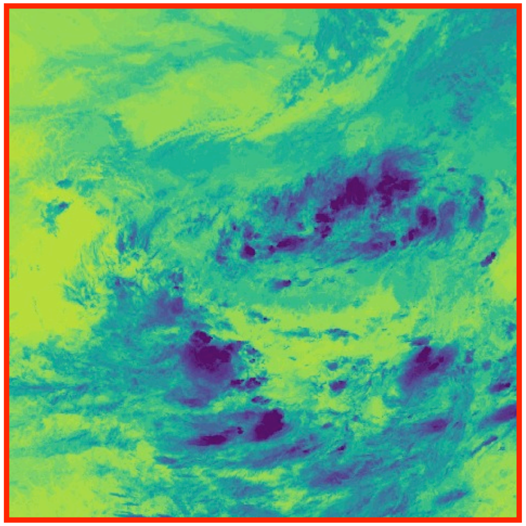
Square grid and blurring problem



Non-overlapping frame



Overlapping frame



Denoised frame

Denoising Model

2. Modified U-Net

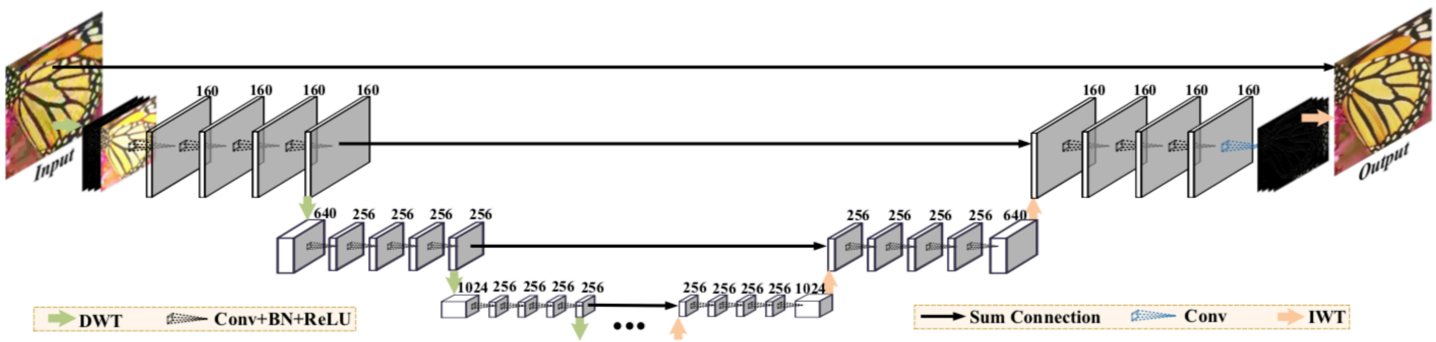
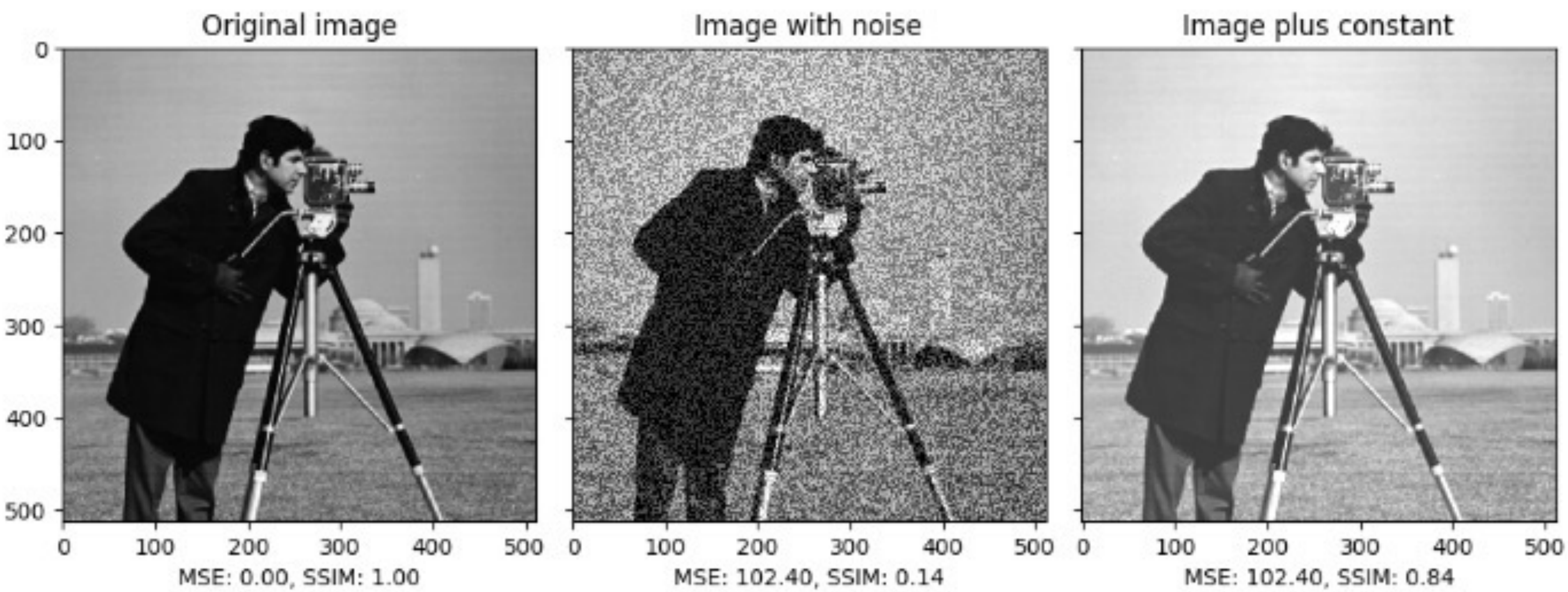


Figure 3. Multi-level wavelet-CNN architecture. It consists two parts: the contracting and expanding subnetworks. Each solid box corresponds to a multi-channel feature map. And the number of channels is annotated on the top of the box. The network depth is 24. Moreover, our MWCNN can be further extended to higher level (e.g., ≥ 4) by duplicating the configuration of the 3rd level subnetwork.

Evaluation Metrics



PSNR: Peak Signal-to-Noise Ratio

$$PSNR(x,y) = 10 * log\left(\frac{P_{max}^2}{\sigma(x,y)^2}\right)$$

SSIM: Structural Similarity Index/Measurement

$$SSIM(x,y) = \left[l(x,y)^{\alpha} \cdot c(x,y)^{\beta} \cdot s(x,y)^{\gamma}\right]$$

Samples of x and y: luminance(l), contrast, structure(s)

$$l(x,y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1}$$

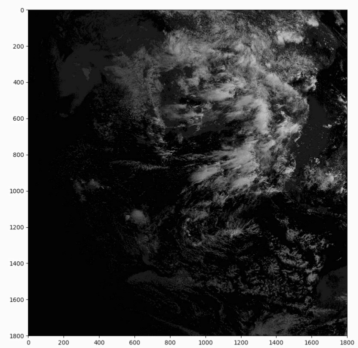
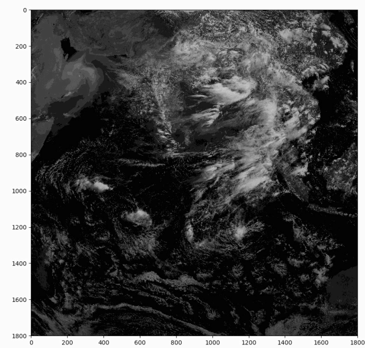
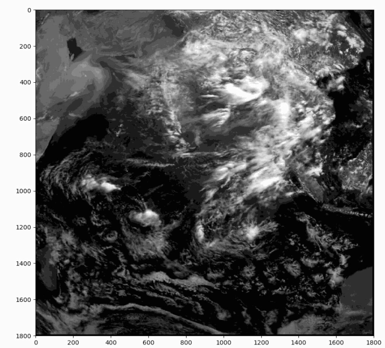
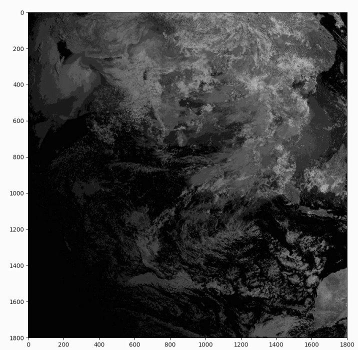
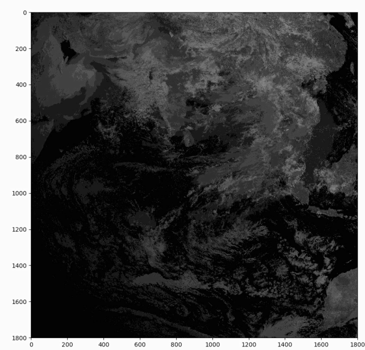
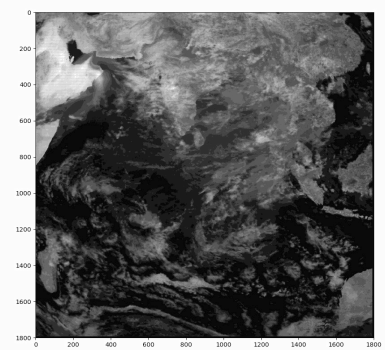
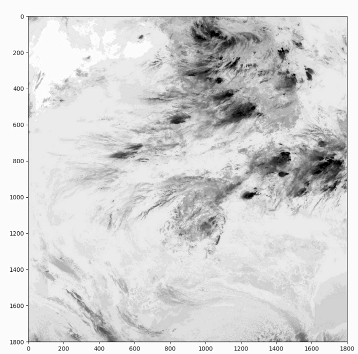
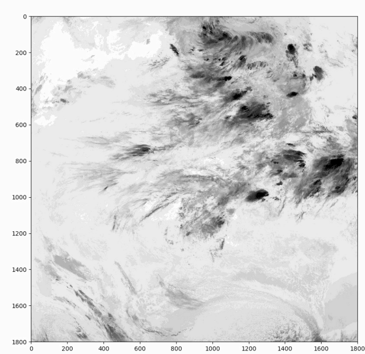
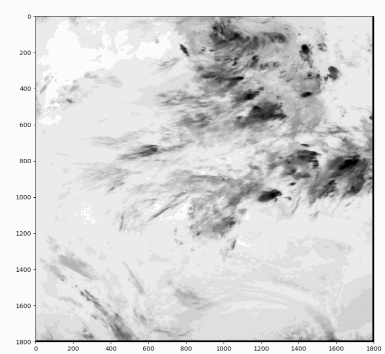
$$c(x,y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2}$$

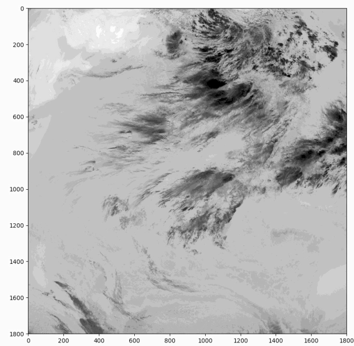
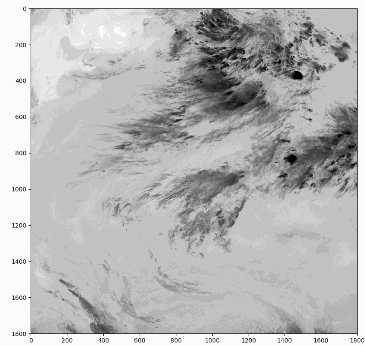
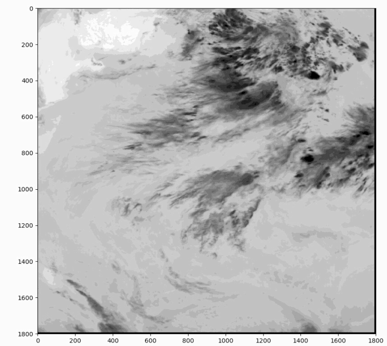
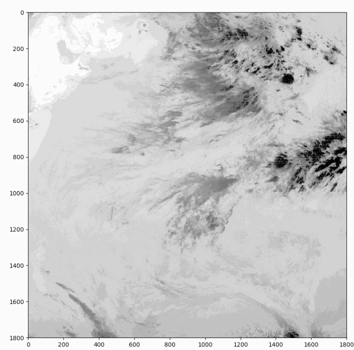
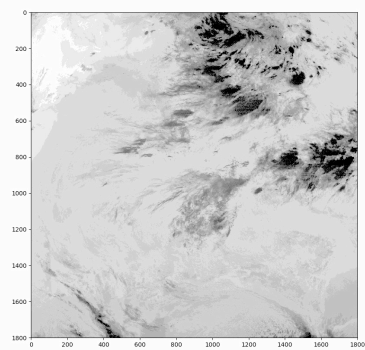
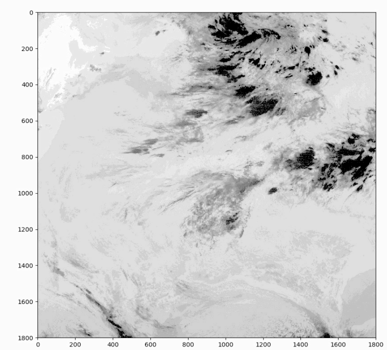
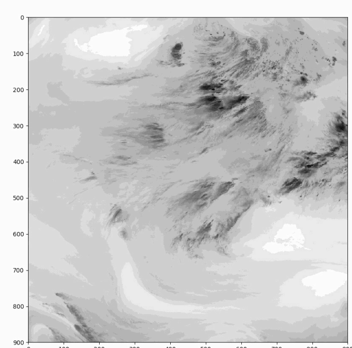
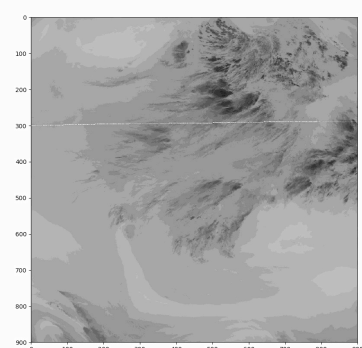
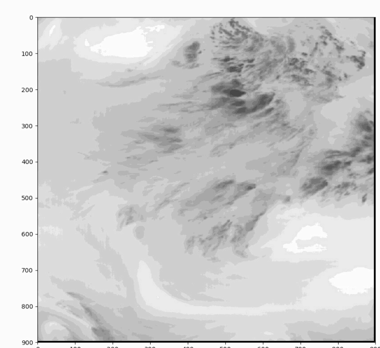
$$s(x,y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3}$$

Results

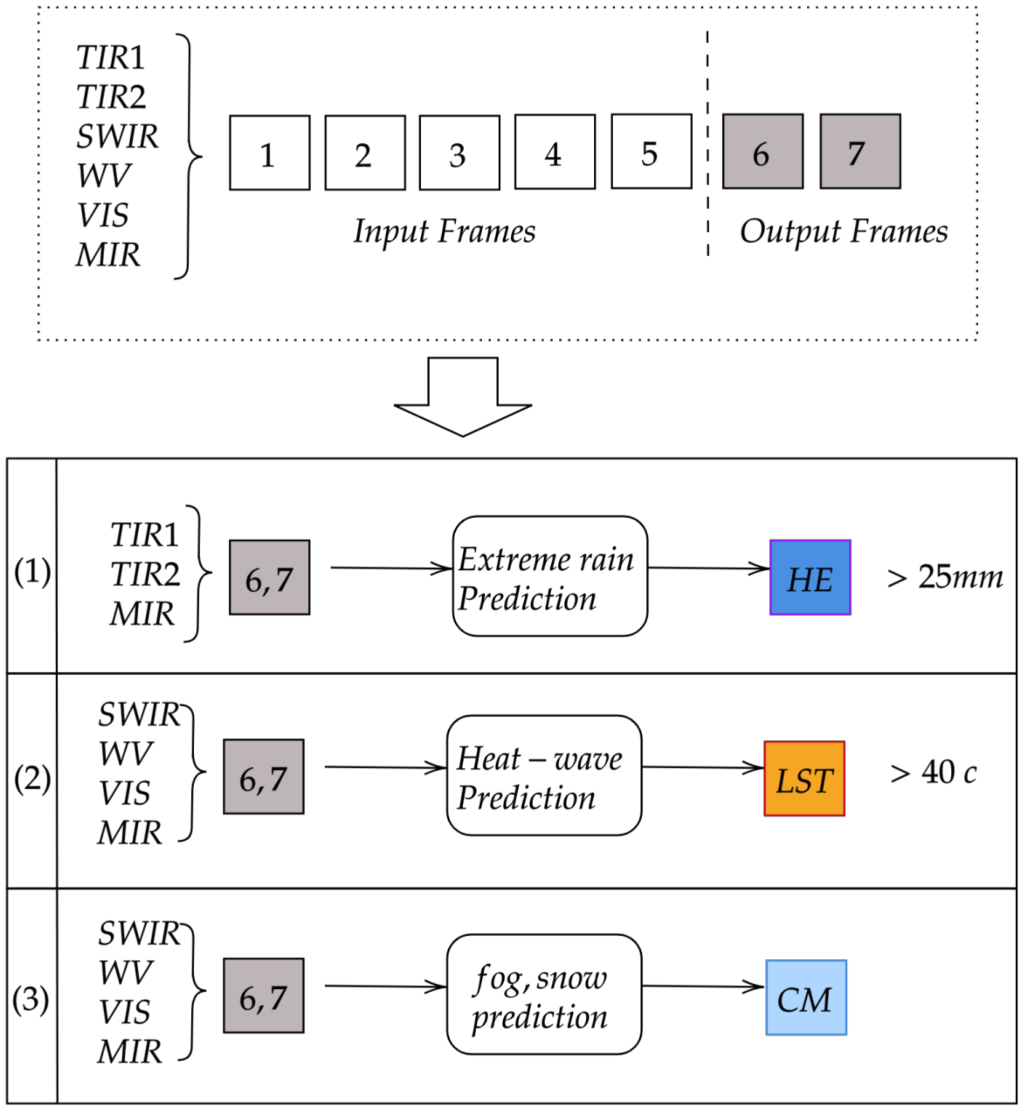
Sr. No.	Dataset Channel	SSIM	PSNR
1	IMG_VIS	0.852	25.413
2	IMG_SWIR	0.801	27.169
3	IMG_TIR1	0.916	22.034
4	IMG_TIR2	0.884	23.564
5	IMG_MIR	0.891	23.879
6	IMG_WV	0.963	26.327

Next slides show sample predictions for 31st July 2018.
Input frames - 10:30 to 12:30; output frame - 13:00

Product	(t-4) th frame	t th frame	Predicted frame
VIS			
SWIR			
TIR1			

Product	(t-4) th frame	t th frame	Predicted frame
TIR2			
MIR			
WV			

Future Work



TIR1
TIR2
SWIR
WV
VIS
MIR
1
2
3
4
5
6
7
Input Frames
Output Frames
(1)
TIR1
TIR2
MIR
6,7
Extreme rain Prediction
HE
> 25mm
(2)
SWIR
WV
VIS
MIR
6,7
Heat – wave Prediction
LST
> 40 c
(3)
SWIR
WV
VIS
MIR
6,7
fog, snow prediction
CM

References

1. Xingjian, S. H. I., et al. “Convolutional LSTM network: A machine learning approach for precipitation nowcasting." *Advances in neural information processing systems*. 2015.

2. Ghaderi, Amir, Borhan M. Sanandaji, and Faezeh Ghaderi. "Deep forecast: deep learning-based spatio-temporal forecasting." *arXiv preprint arXiv:1707.08110* (2017).

3. Zhuang, W. Y., and Wei Ding. "Long-lead prediction of extreme precipitation cluster via a spatiotemporal convolutional neural network." *Proceedings of the 6th International Workshop on Climate Informatics: CI*. 2016.

4. Liu, Yunjie, et al. "Application of deep convolutional neural networks for detecting extreme weather in climate datasets." *arXiv preprint arXiv:1605.01156*(2016).

5. Grover, Aditya, Ashish Kapoor, and Eric Horvitz. "A deep hybrid model for weather forecasting." Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM, 2015.

6. B. Klein, L. Wolf and Y. Afek, "A Dynamic Convolutional Layer for short rangeweather prediction," 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Boston, MA, 2015, pp. 4840-4848.

7. Zaytar, Mohamed Akram, and Chaker El Amrani. "Sequence to sequence weather forecasting with long short term memory recurrent neural networks." Int J Comput Appl 143.11 (2016).

8. Salman, Afan Galih, Bayu Kanigoro, and Yaya Heryadi. "Weather forecasting using deep learning techniques." Advanced Computer Science and Information Systems (ICACSIS), 2015 International Conference on. IEEE, 2015.

9. Grover, Aditya, Ashish Kapoor, and Eric Horvitz. "A deep hybrid model for weather forecasting." Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM, 2015.

References

10. Hossain, Moinul, et al. "Forecasting the weather of Nevada: A deep learning approach." Neural Networks (IJCNN), 2015 International Joint Conference on. IEEE, 2015.

11. Salman, Afan Galih, et al. "Weather Forecasting Using Merged Long Short-term Memory Model." Bulletin of Electrical Engineering and Informatics 7.3 (2018): 377-385.

12. Nhita, Fhira, Deni Saepudin, and Untari Novia Wisesty. "Comparative Study of Moving Average on Rainfall Time Series Data for Rainfall Forecasting Based on Evolving Neural Network Classifier." Computational and Business Intelligence (ISCBI), 2015 3rd International Symposium on. IEEE, 2015.

13. P. Darji, Mohini & Dabhi, Vipul & Prajapati, Harshadkumar. (2015). Rainfall forecasting using neural network: A survey. 10.1109/ICACEA.2015.7164782.

14. Zhang, Xike, et al. "A Novel Hybrid Data-Driven Model for Daily Land Surface Temperature Forecasting Using Long Short-Term Memory Neural Network Based on Ensemble Empirical Mode Decomposition." International journal of environmental research and public health 15.5 (2018): 1032.

15. Karim, Fazle, et al. "LSTM fully convolutional networks for time series classification." IEEE Access 6 (2018): 1662-1669.

16. Kim, Seongchan, et al. "DeepRain: ConvLSTM Network for Precipitation Prediction using Multichannel Radar Data." arXiv preprint arXiv:1711.02316 (2017).

THANK YOU!

QUESTIONS?