

Machine Learning in Atmospheric Sciences - How are we catching up?

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Introduction

- Climate change becoming a growing concern
- Anthropogenic activities; indirectly but severely accelerating climate change
- Extreme weather events are an effect; tropical cyclone (TC), the most destructive
- Machine learning (ML) can help existing weather models
- Satellite data are open-sourced
- Computational resources most powerful
- Early prediction; minimize damage to lives and property





Damaged bus stop due to TC Mandous, HT (online), Dec 11, 2022

House collapses due to TC TAUKTAE, IT (online), May 15, 2021



Tree uprooted due to TC Asani, DC (online), May 12, 2022



Destruction post TC AMPHAN, OUTLOOK (online), May 22, 2020

Datasets

- INSAT-3D images from Meteorological and Oceanographic Satellite Data Archival Centre (MOSDAC)
 - IMAGER payload across six bands of the electromagnetic spectrum
 - Visible (VIS), Medium infrared (MIR), Shortwave infrared (SWIR)
 - Thermal Infrared Level 1 (TIR1), Thermal Infrared Level 2 (TIR2), Water Vapor (WV)
 - Multi-spectral images at a cadence of 30 minutes
- Regional Specialized Meteorological Centre (RSMC), New Delhi, Reports
 - Published annually by IMD
 - Intensity levels of TCs
 - Latitude and longitude positions of the centre of a storm
 - Timeline of each of the stages of the TC
- European Centre for Medium-Range Weather Forecasts (ECMWF)
 - Provides the ECMWF Reanalysis v5 (ERA5) data
 - Hourly estimates of large number of atmospheric, land and oceanic variables
 - Covers the Earth on a grid of 30 kilometers
 - Resolves the atmosphere using 137 levels from surface to a height of 80 kilometers

Intensity classification



DEPRESSION (D)



DEEP DEPRESSION (DD)



CYCLONIC STORM (CS)

TC stage	MSW		
Low pressure area	<31 km/hr		
Depression (D)	31 km/hr to 49 km/hr		
Deep depression (DD)	50 km/hr to 61 km/hr		
Cyclonic storm (CS)	62 km/hr to 88 km/hr		
Severe cyclonic storm (SCS)	89 km/hr to 117 km/hr		
Very severe cyclonic storm (VSCS)	118 km/hr to 166 km/hr		
Extremely severe cyclonic storm (ESCS)	167 km/hr to 221 km/hr		
Super cyclonic storm (SuCS)	>= 222 km/hr		



SEVERE CYCLONIC STORM (SCS)

SUPER CYCLONIC STORM (SuCS)



EXTREMELY SEVERE CYCLONIC STORM (ESCS)







Block diagram of the steps of the multi-class classification problem

Results of intensity classification [5]

		Avg. Acc.	Avg. Pr.	Avg. Recall	Avg. F-Score
Storm	Band	CV Score	CV Score	CV Score	CV Score
AMPHAN	IR1	0.979	0.986	0.965	0.975
	IR2	0.998	0.994	0.984	0.989
	WV	0.974	0.979	0.986	0.982
	MIR	0.967	0.948	0.979	0.963
	ALL	0.994	0.996	0.983	0.989
FANI	IR1	0.997	0.997	0.983	0.990
	IR2	0.971	0.989	0.973	0.981
	WV	0.992	0.993	0.989	0.991
	MIR	0.937	0.911	0.961	0.935
	ALL	0.996	0.986	0.978	0.982
YAAS	IR1	0.998	0.999	0.989	0.994
	IR2	0.998	0.998	0.993	0.995
	WV	0.997	0.996	0.992	0.994
	MIR	0.923	0.914	0.945	0.929
	ALL	0.998	0.994	0.983	0.988
PHAILIN	IR1	0.991	0.986	0.991	0.988
	IR2	0.996	0.998	0.992	0.995
	WV	0.948	0.996	0.991	0.993
	MIR	0.943	0.892	0.998	0.942
	ALL	0.998	0.995	0.981	0.988
MERGED	IR1	0.993	0.990	0.981	0.985
	IR2	0.997	0.993	0.997	0.995
	WV	0.992	0.991	0.997	0.994
	MIR	0.998	0.991	0.976	0.983
	ALL	0.991	0.998	0.989	0.993

Pal, et al, 2022, CVIP, https://doi.org/10.1007/978-3-031-31407-0_27 6

Track prediction

- Path or route followed by a TC
- Given a specific time interval, it is expressed in terms of latitude and longitude
- Helps to predict the point of landfall and aid in prior evacuation
- Posed as a multi-output (latitude and longitude) regression problem over time
- ML algorithms for sequence modeling can be used
- INSAT 3D images from MOSDAC along with ERA5 data for wind and pressure
- RSMC New Delhi reports for data labeling and data preparation
- Recurrent Neural Network (RNN)
- Long Short Term Memory (LSTM)
- Gated Recurrent Unit (GRU)



Observed track of DD over BoB during March 3 to March 6, 2022

Track prediction



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Acknowledgments

The authors thank MOSDAC for providing free access to INSAT-3D data.

DOI: 10.19038/SAC/10/3DIMG_L1C_SGP. For more information, please visit https://mosdac.gov.in."

Thank you