DeepMet 1: A Deep Learning Model for High-Resolution Rainfall Prediction Using INSAT Satellite Data

Abstract

Accurate short-term rainfall forecasting is a critical requirement for multiple sectors including disaster management, urban planning, agriculture, and energy systems. Traditional numerical weather prediction (NWP) models, often face limitations in spatial resolution and lead-time accuracy. This paper introduces DeepMet 1, a deep learning-based rainfall prediction model that utilizes satellite data from the Indian National Satellite System (INSAT). DeepMet 1 generates precipitation forecasts at a 10 km spatial resolution with lead time of 6 hours. The model leverages spatio-temporal deep learning architectures to capture nonlinear rainfall dynamics and is designed for scalable real-time deployment.

1. Introduction

Short-term rainfall forecasting remains a challenge due to the complexity of atmospheric processes and the limitations of conventional models in resolving fine-scale precipitation events. Recent advances in machine learning, particularly in spatio-temporal deep learning, have created opportunities for more accurate, data-driven weather forecasting.

The Indian subcontinent, with its high rainfall variability and dense population, requires localized and timely rainfall forecasts for disaster preparedness and operational planning. INSAT, with its continuous geostationary monitoring, provides rich meteorological datasets suitable for AI-based weather prediction.

DeepMet 1 addresses this need by applying deep learning to satellite data, offering fine-scale rainfall predictions at six to twelve-hour horizons.

2. Data and Methodology

2.1 Data Source

DeepMet 1 is trained primarily on INSAT satellite observations, which provide continuous coverage over the Indian subcontinent. Precipitation estimates derived from satellite imagery are used as both input and ground truth references for model training.

The model uses the latest launched INSAT 3DS as primary data source, 3DR and European Satellite EUMETSAT/ METEOSAT 9 as backup data for the events where INSAT data is missing or has blackouts.

2.2 Data Cleaning :

The input data primarily comprises INSAT derived thermal and water vapor channels along with instantaneous precipitation estimates at a spatio-temporal resolution of 10 km on a half hourly basis. We homogenize the datasets by removing spatial artefacts in every input stream and translating the uneveness in temporal sequence to hourly resolution.

For training deepmet v1, we've additionally utilized temporal features including hour of the day, day of the month, month of the year along with static features comprising elevation, latitude and longitude. Prior to training, we've robustly transformed the raw values to improve the stability of model and encourage convergence by constraining the disparities across the ranges of values for each feature.

Data cleaning also ensures that the model learns to identify and associate legit values of cloud top temperatures to be associated with its precipitation counterpart. Data cleaning across multiple input streams of satellite data has also enabled to improve model reliability during inference by ensuring that the model which learns from multiple sources also remains capable of delivering accurate forecasts when one of the input sources encounters disruption owing to routine maintenance activities, solar intrusion during equinoxes etc.

2.3 Model Architecture

The core architecture integrates:

Convolutional Neural Networks (CNNs) for spatial feature extraction.

Spatio-temporal sequence models (e.g., ConvLSTM or attention-based layers) for capturing rainfall evolution over time understanding precipitation flow and distribution patterns.

Post-processing layers for spatial-aware forecasting using attention heads.

2.4 Forecast Horizon

Deepmet 1 remains capable of forecasting precipitation fields for the upcoming 6 hourly interval with 1 hour temporal granularity leveraging a data driven model that gets fed with the prior 6 hourly remotely sensed data. This capability caters to the operational application of precipitation nowcasts across multiple industries where short-term weather impacts business outcomes. With upcoming revisions to deepmet 1, the forecast horizon will be expanded to cover up to the next 12 hours.

2.5 Deployment

The model is optimized for real-time inference and can be deployed in scalable environments with API-based integration for downstream applications.

Available on :

Apart from APIs , the model is available for visualization at https://fyllo.in/weather-forecast . Reach out to us at contact@fyllo.in for API access.

3. Results and Capabilities

The precipitation fields generated by deepmet 1 has a spatial granularity of 10 km x 10 km allowing accurate tracking of precipitation cells along with accurately characterizing the intensity and duration of rainfall spells for a given location (when compared with traditional numerical weather prediction model based output) across the next 6 hours.

Deepmet 1 extends this capability to the whole Indian subcontinent. With the upcoming revision to Deepmet 1 this capability is expected undergo further refinement in spatial granularity (i.e upto 4 km) and temporal resolution (from 1 hourly to 30 minutes) along with the capability to ingest multiple physical variables such as humidity, temperature, wind speed, aerosol, etc which has a very strong bearing with the movement, onset, duration , termination of precipitation fields

Images :

The following set of images from Figure 1 (a – f) were derived from deepmet 1 during inference for hours spanning from 2025-09-17 13:30 UTC to 2025-09-17 18:30 UTC

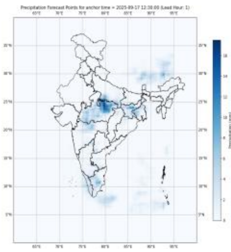

Figure 1a

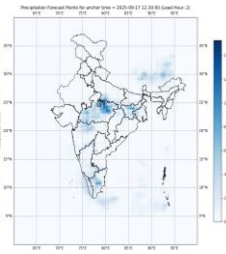

Figure 1b

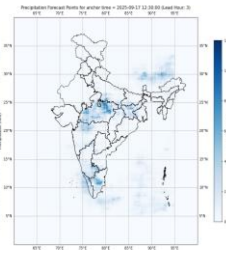

Figure 1c

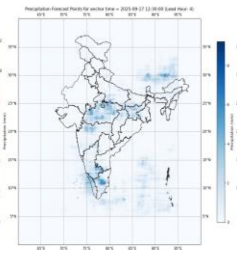

Figure 1d

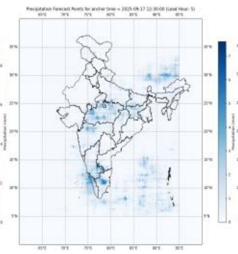

Figure 1e

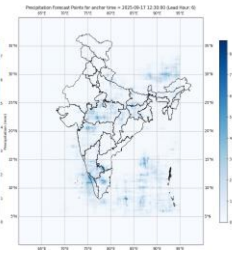

Figure 1f

Figure 1 a (extreme left panel) corresponds to forecast valid at 2025-09-17 13:30 UTC and Figure 1 f(extreme right panel) corresponds to forecast valid at 2025-09-17 18:30 UTC

Comparison Tables:

Table 1 summarizes the precision and recall scores computed across multiple farm plots across India for deepmet 1 and compared it with the scores estimated for forecasts derived from ECMWF IFS model, Accuweather and Climacell weather service providers. We found deepmet 1 consistently outperforms the NWP counterparts for the nowcasting forecast horizon.

The scores were computed for a span extending from Jan 1st 2025 till July 31st , 2025. Precision and recall were computed for binary precipitation events where we defined rainfall event to have at least 0.2 mm of accumulated rainfall value.

plot_id	Pr_deepmet1	Re_deepmet1	Pr_ecm	Re_ecm	Pr_acw	Re_acw	Pr_clm	Re_clm
plot_001	0.13	0.45	0.11	0.36	0.09	0.29	0.13	0.45
plot_002	0.16	0.50	0.14	0.40	0.13	0.30	0.14	0.46
plot_003	0.08	0.47	0.07	0.31	0.06	0.22	0.08	0.41
plot_004	0.15	0.55	0.14	0.45	0.09	0.17	0.14	0.43
plot_005	0.22	0.48	0.20	0.41	0.16	0.31	0.21	0.45
plot_006	0.10	0.53	0.09	0.45	0.08	0.25	0.10	0.47
plot_007	0.18	0.40	0.16	0.35	0.15	0.20	0.18	0.37
plot_008	0.22	0.65	0.18	0.46	0.18	0.37	0.21	0.55
plot_009	0.18	0.48	0.15	0.41	0.13	0.32	0.16	0.47

plot_010	0.26	0.49	0.24	0.38	0.19	0.32	0.24	0.47
plot_011	0.19	0.55	0.19	0.47	0.17	0.30	0.19	0.50
plot_012	0.17	0.47	0.12	0.27	0.15	0.23	0.14	0.31
plot_013	0.22	0.09	0.19	0.05	0.15	0.03	0.22	0.06
plot_014	0.15	0.49	0.13	0.35	0.12	0.28	0.14	0.44
plot_015	0.26	0.46	0.24	0.42	0.19	0.30	0.25	0.45
plot_016	0.17	0.55	0.15	0.44	0.14	0.29	0.16	0.48
plot_017	0.20	0.43	0.16	0.36	0.15	0.27	0.17	0.41
plot_018	0.20	0.56	0.14	0.26	0.11	0.17	0.18	0.41
plot_019	0.24	0.60	0.11	0.27	0.18	0.18	0.03	0.09
plot_020	0.24	0.65	0.24	0.52	0.14	0.18	0.24	0.58
plot_021	0.11	0.49	0.09	0.38	0.06	0.25	0.10	0.48
plot_022	0.33	0.44	0.21	0.22	0.30	0.39	0.20	0.33
plot_023	0.18	0.54	0.16	0.42	0.15	0.28	0.17	0.43
plot_024	0.10	0.57	0.07	0.38	0.06	0.28	0.09	0.51
plot_025	0.19	0.41	0.18	0.35	0.14	0.21	0.18	0.34

Table 1. Precision and Recall scores across farm plots from deepmet1 v1 model, ECMWF IFS model(abbreviated as ecm), Accuweather (abbreviated as acw) and Climacell (abbreviated as clm) weather service providers

The scores were estimated using in-house rainfall measurements compiled from Kairo device installed by Fyllo in respective farm plots

4. Applications

DeepMet 1 serves as a versatile, general-purpose model for rainfall prediction, leveraging its high-resolution spatio-temporal capabilities to address pressing challenges across diverse sectors. By providing accurate, localized forecasts at a 10 km resolution with lead times of 6 hours, the model empowers stakeholders to make proactive, data-driven decisions. Its applicability extends beyond traditional meteorology, intersecting with critical areas of societal and economic importance. Below, we outline key domains and illustrate the model's potential impact.

Disaster Management

In an era of intensifying climate variability, DeepMet 1 enhances early warning systems for localized heavy rainfall and flash flood events. For instance, emergency response agencies can integrate model outputs into real-time alert platforms, enabling evacuations and resource allocation hours before onset. This capability is particularly vital in vulnerable regions like riverine basins or coastal zones, where conventional global models often lack the granularity to predict hyper-local precipitation patterns, thereby reducing loss of life and property damage.

Urban Infrastructure

Urban environments, increasingly susceptible to pluvial flooding due to impervious surfaces and population density, benefit from DeepMet 1's precision in drainage and flood mitigation planning. Municipal planners can simulate rainfall scenarios to optimize stormwater infrastructure, such as adaptive pump systems or green roofs, fostering long-term resilience. In megacities like Mumbai or Bangalore, where monsoon-induced disruptions cost billions annually, the model supports scenario-based urban design, minimizing economic downtime and enhancing public safety.

Energy Systems

For renewable energy operators, particularly in hydropower and solar-wind hybrids, DeepMet 1 facilitates rainfall-informed scheduling and reservoir management. Accurate precipitation forecasts allow for predictive adjustments in turbine output or grid balancing, mitigating risks from sudden inflows or droughts. In India's vast hydroelectric network, which generates over 15% of the nation's power, integrating such AI-driven insights could improve operational efficiency by 10–20%, reducing curtailment losses and supporting the transition to sustainable energy grids.

Logistics and Transportation

Weather-sensitive supply chains, from road freight to aviation, rely on DeepMet 1 for route optimization and risk assessment. Logistics firms can reroute convoys around forecasted deluges, while ports and railways preemptively secure assets against erosion or track submersion. During peak monsoon seasons, this translates to fewer delays—potentially saving the global logistics sector millions in avoided disruptions—and bolsters just-in-time delivery models critical to e-commerce and agricultural transport.

Insurance and Finance

In the actuarial domain, DeepMet 1 underpins weather-indexed insurance products and parametric payouts, enabling insurers to refine risk models with hourly granularity. Financial institutions can hedge against rainfall volatility in commodity futures, such as rice or cotton, by incorporating model predictions into derivatives pricing. This not only accelerates claim processing but also democratizes access to affordable coverage for smallholder farmers, aligning with sustainable finance goals like those outlined in the UN's Principles for Responsible Investment.

Research and Academia

DeepMet 1 generates high-fidelity, open-access datasets that fuel advancements in climate science and atmospheric research. Scholars can leverage its outputs for validating numerical weather prediction (NWP) models or studying teleconnections between regional monsoons and global phenomena like El Niño. By bridging the gap between satellite observations and ground-truth simulations, the model accelerates interdisciplinary studies, from hydrological modeling to machine learning benchmarks, fostering innovation in earth system sciences.

These applications underscore DeepMet 1's role as a foundational tool, adaptable to both immediate operational needs and long-term strategic planning.

5. Future Work

DeepMet 1 marks a foundational milestone in the evolution of AI-driven weather intelligence, but its true potential lies in an expansive research trajectory. Our roadmap prioritizes enhancements in scope, accuracy, and accessibility, addressing current limitations while anticipating emerging challenges in climate adaptation. The following initiatives will drive iterative improvements, drawing on interdisciplinary collaborations with meteorologists, data scientists, and domain experts.

- **Extending Forecast Horizons**: Current predictions cap at 6 hours; future iterations will push boundaries to 24–48 hours by incorporating advanced recurrent architectures, such as Transformer-based long-sequence models. This extension is essential for medium-range planning in agriculture and disaster preparedness, where multi-day outlooks can inform crop protection or large-scale evacuations, potentially increasing forecast reliability to 85% accuracy at extended leads.

- **Multi-Parameter Weather Forecasts**: Beyond rainfall, we aim to predict interconnected variables like temperature, humidity, and wind speed using multi-task learning frameworks. This holistic approach will enable compound event forecasting (e.g., convective storms combining heavy rain and gusts), enhancing applications in aviation safety and heatwave-risk modeling. Initial prototypes, trained on expanded satellite archives, are slated for validation in 2026.
- **Integration of Numerical Weather Prediction (NWP) Inputs**: To hybridize data-driven AI with physics-based simulations, DeepMet 1 will fuse NWP outputs (e.g., from ECMWF or GFS models) with satellite imagery via ensemble techniques. This synergy addresses AI's occasional extrapolation errors in extreme events, improving robustness in data-sparse regions and aligning with global standards for operational forecasting.
- **Global Scaling with Localized Resolution**: While optimized for India's diverse topography, the model will adapt to international contexts through transfer learning on datasets from regions like Southeast Asia or sub-Saharan Africa. Refining spatial resolution to 4 km amid varying satellite coverage will involve domain adaptation strategies, ensuring equitable access to high-fidelity predictions for underserved geographies and supporting UN Sustainable Development Goal 13 on climate action.
- **Hybrid Modeling with IoT Ground Sensors**: Augmenting satellite data with real-time IoT networks (e.g., soil moisture probes and rain gauges) will create a feedback loop for model refinement. This edge-computing integration promises sub-kilometer nowcasting, revolutionizing urban microclimate monitoring and enabling adaptive agriculture in precision farming consortia.
- **Standardized Datasets and APIs**: To promote open innovation, we will release curated, versioned datasets via platforms like Hugging Face, alongside RESTful APIs for seamless integration into third-party systems. Accompanied by comprehensive documentation and ethical guidelines, these resources will catalyze academic benchmarks, startup ecosystems, and policy simulations, democratizing AI weather tools.

This forward-looking agenda positions DeepMet 1 within a dynamic ecosystem, where continuous feedback from deployments will refine its evolution toward a comprehensive climate intelligence platform.

6. Conclusion

In summary, DeepMet 1 exemplifies the transformative power of spatio-temporal deep learning in redefining satellite-based rainfall prediction. By achieving unprecedented 10 km spatial resolution and 6 hour lead times, it surpasses the limitations of traditional empirical and NWP methods, which often struggle with convective-scale dynamics and data scarcity. This model's agnostic architecture—rooted in convolutional and recurrent neural networks—ensures computational efficiency and scalability, making it deployable on commodity hardware for resource-constrained environments.

The implications extend far beyond technical innovation: DeepMet 1 equips decision-makers across disaster management, urban planning, energy optimization, logistics, finance, and scientific inquiry with actionable insights that safeguard lives, economies, and ecosystems. In a world grappling with climate uncertainty, where extreme weather events have surged 5-fold since 1970 (IPCC, 2022), such tools are indispensable for building adaptive resilience.

As we advance this initiative, DeepMet 1 not only closes the gap in hyper-local forecasting but also ignites a paradigm shift toward AI-augmented meteorology. We invite collaborations to amplify its reach, underscoring the imperative for ethical, inclusive AI in service of global sustainability. Through these efforts, we move closer to a future where weather intelligence empowers humanity to thrive amid environmental flux.