ODE-RNN Based Flood Forecasting model

1. Introduction:-

The Mahanadi river basin is one of the largest and most flood-prone basins in India. It has very large catchment area, frequency and intensity of rain events are increasing due to climate change. The area is suffering from multiple recurrent disasters due to the Mahanadi delta in Odisha is adjacent to it. The Hirakud Dam created in 1953 was meant to regulate the excess waters, which were expected to decrease flooding. While it appeared to reduce flooding extensively in the early years, there has been a recent trend towards increased intensity of flooding due to siltation, rainfall intensity and incompetency of the dam infrastructure. This led to multiple catastrophic floods in the basin in 2020 and 2021, where millions of people suffered the inundation experiences despite only receiving approximately eight hours of lead time from existing early warning systems.

In response to this situation, the Adaptive Climate Technology (ACT) program and Government of Odisha began developing the next-generation flood-forewarning system, which includes climate-adjusted modeling with local forecasting and better hydrological simulation as part of the approach. Our work, a detailed study of an advanced ODE-RNN based flood forecasting model, which refers to an ODE based therapeutic machine learning architecture capable of learning from irregular time-series data, supporting early warning systems (EWS) with lead times of 48-72 hours is an integral part of the activities.

2. Real-World Problem Context:-

Climate change has altered the hydrological behavior of the Mahanadi Basin. Floods that were previously considered 1-in-1000-year events have occurred 10 times since Hirakud Dam's construction. Odisha's downstream delta is home to over 10 million rural people most of whom live in poverty and depends on climate-sensitive livelihoods including fishing and agriculture. Getting hit by repeated floods comes with significant human and economic loss. Presently, the forecasting system does not offer enough lead time warning to allow for targeted timely evacuations and preparedness measures are as a result poor. Our intervention at ACT was to develop a new hydrology model that was able to capture localized weather inputs (like forecasting precipitation), the terrain data and the flows of the river that accounted for monsoonal (extreme weather) behaviours to enhance the forecasting predictions.

3. ODE-RNN Methodology:-

<u>Data and Features:-</u>
We have 3050 rainfall entries, 3045 runoff entries from 158 stations, Discharge data from 12 stations, excluding Hirakud, Target Variable: Hirakud inflow (m^3/s). Input features include: Mean rainfall, Mean runoff, Mean discharge (excluding Hirakud)

<u>Preprocessing:-</u>
Removed initial 5 days of rainfall to account for antecedent conditions. Normalized all variables using Min-Max scaling.

80-20 split for training and testing, preserving time order. Used a sliding window of 10 steps to form temporal sequences for the model.

Model Architecture:-

The ODE-RNN model combines a neural ODE to evolve hidden states continuously between observations and a traditional RNN update at observation points. This architecture overcomes the limitations of standard RNNs, which assume uniformly spaced data, struggling with missing values or irregular timestamps, Cannot model real-time changes between observations.

In contrast, ODE-RNN models continuous-time latent dynamics, learns non-linear relationships,handles irregular sampling seamlessly.

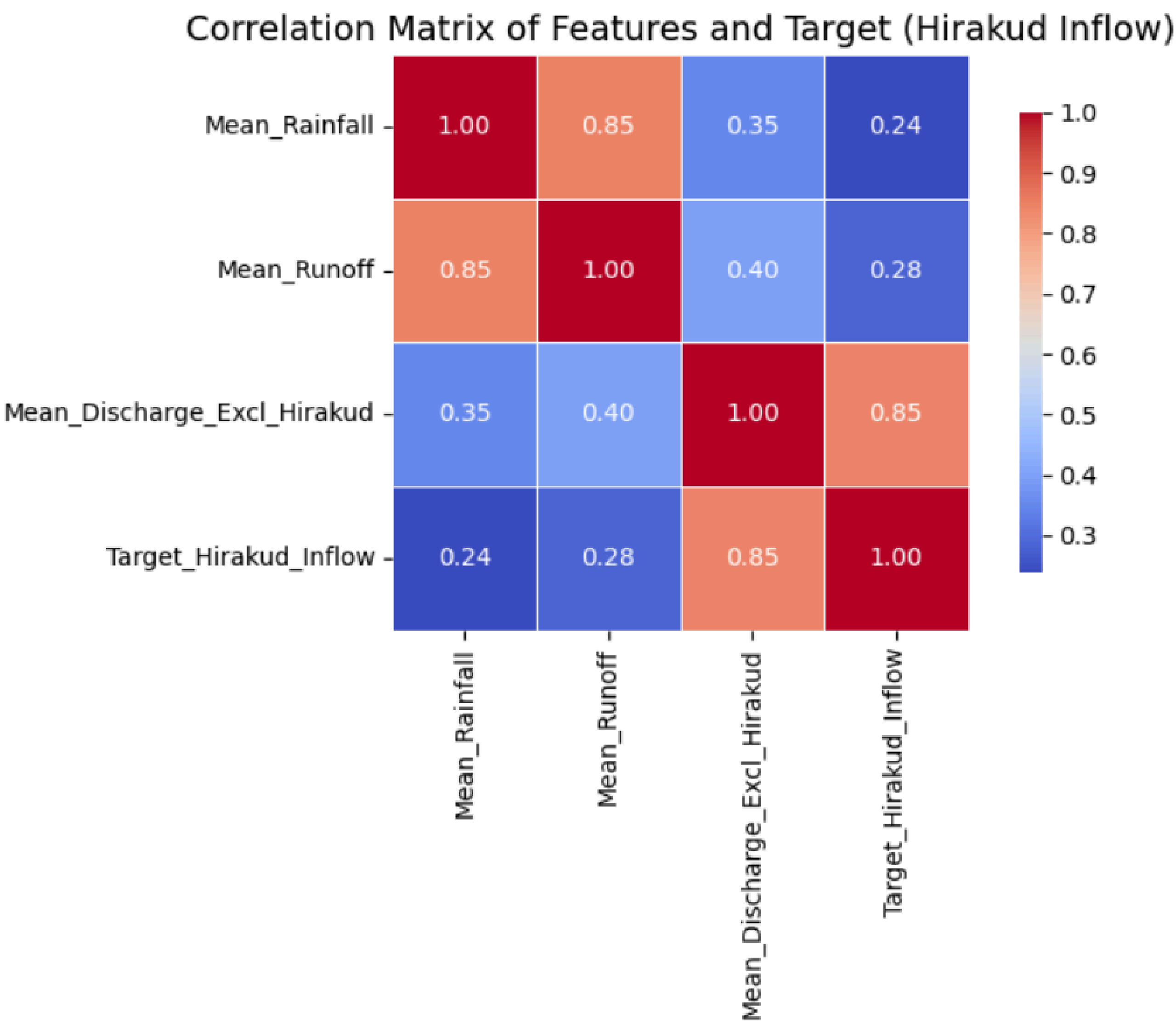
4. Enhancing the Model with Latent ODEs:-

To model uncertainty and improve generative capability, we extended our model using Latent ODEs that introduces a latent variable z0 to generate full trajectories. An ODE-RNN encoder estimates the posterior of z0 using variational inference. Enables uncertainty quantification, interpolation, and long-term forecasting. When combined with Poisson process likelihoods, the model can handle event-driven data (e.g., real-time sensor activations), improve forecasting under sparse observation regimes.

5. Findings and Performance:-

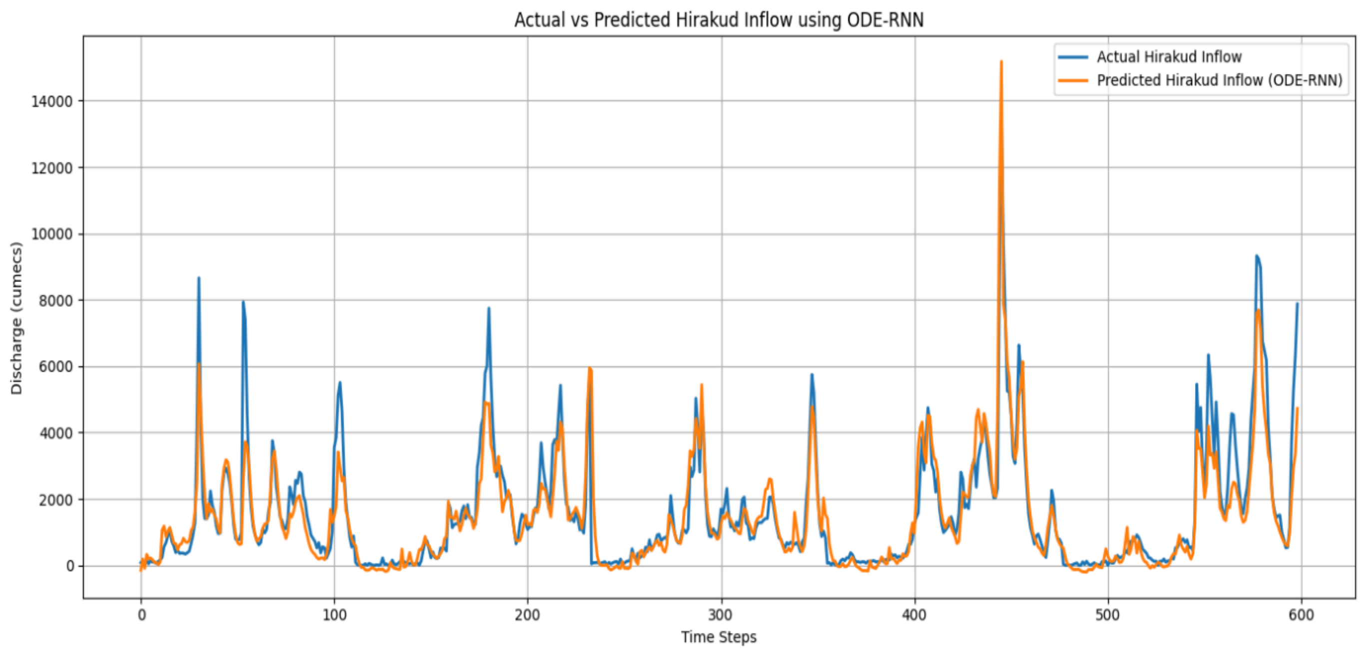
Time Series Insights:-

Discharge (excluding Hirakud) had the highest correlation with inflow (0.85). Rainfall and runoff showed seasonal patterns; inflow had sharp spikes aligning with monsoon events.



Model Results:-

ODE-RNN and Latent ODEs outperformed GRUs and standard RNNs. Showed strong extrapolation performance, even on sparse or noisy data. Provided insights into the underlying temporal structure of flood dynamics.



6. Alignment with Odisha Government's Vision:-

Our work complements ACT and the Government of Odisha's goals:

Provides a model of adaptive, forecast-driven decision-making. Recognizes a shift from reactive flood management to proactive flood management. Enables 48–72 hour early warnings, which are critical for evacuation and asset protection. Increases resilience for vulnerable rural communities through timely alerts.

ACT's system provides state and district decision-making support, which will reduce mortality and loss of livelihoods from flooding events. Build residents' confidence in responding to climate-based risk.

7. Conclusion:-

This project illustrates the application of advanced models such as ODE-RNNs to the practical challenge of operational flood forecasting. Not only does the model succeed in capturing the complex and nonlinear interactions in the hydrological systems, and also in its ability to adapt to irregular data patterns, but the model has the ability to generate timely, reliable forecasts necessary for Early Warning Systems. As climate change initiatives interact with flood frequency and magnitude, these predictive capabilities will be important for disaster risk reduction, to saving lives, as well as building infrastructure to withstand the changes. In addition, with ongoing integration and support from ACT, our system for ODE-RNN forecasting has the potential to contribute to flood resilience in the Mahanadi Basin, in a meaningful way.