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Smart River, India: A Multimodal AI Framework for Streamflow Forecasting and Hydrological Risk Prediction

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ABSTRACT: River flow and the hydrology system always create positive information on how the water system should be handled. The process here supports the control facilities of flood and health plans to maintain their protection for local habitat. In countries like India, the system here is more critical based on the weather, which poses a great deal of river-based issues for the people nearby.

In the Indian subcontinent, rain does not always happen in every area on the places and particular Times. Amazing part of the process Southeast monsoon session which creates the words like Ganga as well as Godavari major floods at least once a time in a year.

There is some other hydrology models based on physical rules create the particular nature of processing the complex behaviour of large river systems. The models need to be carefully tuned to maintain the detailed data-based setting in many developing areas, which in a normal way not normally accessible.

To address these all challenges, this paper here presents 'Smart River, India', a novel multimodal artificial intelligence framework to maintain designed for continuous streamflow-based forecasting as well as real-time hydrological risk classification herein. The proposed architecture always maintains concurrently processes 2D spatial remote sensing data via Convolutional Neural Networks (CNNs), 1D temporal hydro-meteorological sequences which here using Long Short-Term Memory (LSTM) or Transformer networks, as well as static catchment attributes through Multi-Layer Perceptrons (MLPs). Evaluated based nature of such aspects across the contrasting terrains of the Brahmaputra & Godavari river basins, this particular multimodal fusion effectively captures extreme monsoon responses here. The framework here shown outperforms traditional & unimodal deep learning baselines, achieving more of a peak Nash-Sutcliffe Efficiency (NSE) of 0.94 as well as providing highly reliable flood risk categorization to support regional disaster management.

1. INTRODUCTION

In the land-based new population growth, more problems arise based on the changes. climate based shift problems for water security in India. Indian economy relies on farming's because of that; hydropower matters the most. In a year, about 4 months of monsoon deliver over 80% of rainfall.

The land and height of the Indian continent create more variation, especially in the Northern region of the Himalaya. The plateau structure in the south is not as simple because of the changes and the rainfall, which creates more unevenness based on the areas, which are region-specific.

The result shows much higher version of availability of water based on the flooding conditions of the Ganga and Brahmaputra. Some of the Year in nature, why is it stays dry and contents multiyear problems, which create hydrological risk. Early alerts of flood could solve the situation under India's disaster management policy in India.

In the past, there have been two kinds of modelling based on empirical and conceptual methods. There are the best tools who is to be more physical in nature, like SWAT and MIKE-SHE. These models create a grounded understanding of conservation across India and do not struggle in daily use.

The process-based model data, including hydraulic trade, to understand the vegetation indicators limit their usefulness, especially here, when fast decisions are needed (Ahmad et al., 2025). In many regions of India, uncertain weather conditions always stay in one single place, but they can spread based on different calculative natures; however, physical models are available. With the help of machine learning and big data digestion, Artificial Intelligence can create more changes for the current model of the water system (Sit et al., 2020; Silwal, n.d.).

The method is not highly dependent on strict water physics rules for year-long data-driven models. Instead, it learns how land signals and how rivers behave relate to weather. For example, inputs such as rain and air temperature can be related to outputs such as runoff and streamflow.

The overall method is not very dependent On the Water physics on year driven data models. But the process utilises land signals and weather systems to understand the input of such air and rain policies to maintain the output in a positive way. In the last 10 years, deep learning models for rainfall studies have created different networks such as RNN and LSTM. They can process large databases and model the physical equations in many tests (Kratzert et al., 2019; Wilbrand et al., 2023). There are different models of transformer mechanisms, and long-term patterns have a limitation in processing sequences one by one (Tao et al., 2024; Paternina-Verona, n.d.).

The deep learning hydrology system creates a particular channel to understand the research-based station for groundwater (Jesus, n.d.; Workneh, n.d.). The setup of such aspects requires a lot of information tables to understand satellite image so the cloud areas in different locations. This actually helps the soil moisture system fish Geography inputs based on the digital elevation model to cover land shift.

The deep learning multimodal model can help here to understand the different types of input, which are different, to create a particular view. The process of creating a remote sensing image can be linked with other time-pattern transformers. In this way, the model can be combined with the river system for better output (Shamsuddin et al., 2024; Demiray, n.d.; Li, n.d.). The work in this paper, Smart River India, creates a multi-model AI system to understand the forecasting policy in different regions across the country.

First, it builds one deep learning model that uses several inputs at once. These include time-based weather data, satellite-based indices tied to space, and fixed land- and water-related factors. Second, it checks how well this system compares with older single-source deep models. Examples include LSTM used on its own and CNN used on its own. It also compares against common machine learning baselines. Third, it tests forecast quality during very high flow periods. This part focuses on floods and uses forecasts made for more than one step ahead. Fourth, it offers a way to sort hydrological risk. The aim is to help agencies make choices during real-time operations for disaster management in India.

LSTM and CNN create a deep learning model to understand weather data and satellite data to maintain different factors for comparison against a machine learning baseline. The test showcases hydrological risk to understand the real time operation disaster management systems in India. Overall, this paper applies different AI-based ideas to a large data set Water Commission system in India.

2. LITERATURE REVIEW

Current structure of advancements in hydrology shows a shift from idea-based models to data-driven approaches in this process of the study at hand in this paper. Normally, simpler machine learning techniques here always including Artificial Neural Networks as well as Support Vector Regression and Random Forests development, were essential to begin with.

Research conducted by Sharma (n.d.) suggests that mostly combining Random Forests and SVR dataset in this particular way can update flood forecasting process here over traditional way based physical models here. However, in current way these particular methods fail to achieve to capture temporal dependencies, which are here mostly crucial in hydrology system in this nature.

To address this overseen situation, most of the researchers hereon adopted recurrent neural networks, mainly Long Short-Term Memory models here which better accommodate the relationships status within time steps. For this manner, Kratzert et al. (2019) trained an LSTM process on diverse nature of Indian's basins using the CAMELS dataset by achieving superior and overall results which are needed to compared for process-based models to tailored for individual watersheds situations in different regions of the country. Similar studies here, including those by researcher Willbrand et al. (2023), who have extended LSTM applications to various regions of the country.

Despite different nature of overall effectiveness, LSTMs process here on can struggle with sequences & parallel based processing during training system in here to maintain the process further on. Consequently, transformer-based basin models in India have been greatly introduced to hydrological forecasting for detail water-based situations on a yearly basis. Utilising multi-head attention related, transformers based efficiently analyse based situation numerous past time-based steps on without mostly relying on mostly on their temporal distance based here process. Feizi (n.d.) and Tao et al. (2024) reported more significant improvements with in modelling based long-term seasonal trends & with transformer-based variants like PatchTST.

Simultaneously, on this manner convolutional neural networks here have mostly gained traction for detail manner of spatial tasks. By maintaining and integrating remote based sensing data, CNNs model hereon spatial based structures always influenced by environmental based factors such as soil moisture as well as vegetation. Bentivoglio et al. (2022) here on this matter of study highlighted over their effective and positive use in flood-related mapping structure, showing how convolutions enrich model learning maintains flow routes shaped by topography. Li (n.d.) which here proposed a synergistic CNN-LSTM framework-based structure, were CNNs extract features from precipitation data.

The trend here based on towards multimodal deep learning is mostly evident, merging multiple data forms here for enhanced modelling structure. Shamsuddin et al. (2024) showcased that there's a particular nature of different types of transition from traditional multi-criteria decision to maintain methods to AI-driven uses process here that here mainly adapt to evolving a more suitable nature of climate patterns, mostly overviewed by Sankaranarayanan et al. (2019) & Zhang et al. (2023). Ahmad et al. (2025) as well mostly here achieved a high accuracy level here in flood-based susceptibility mapping structure through a method.

While numerous more studies here on exist on temporal (e.g., LSTM) & spatial (e.g., CNN) models, a nature of multimodal design here that can concurrently incorporate gauge readings to understand satellite imagery as well as topographical data bases for streamflow forecasting to find out the flood risk prediction which here always remains scarce, particularly for India.

2.1 Evolution of Hydrological Forecasting Methods

Classical and Process-Based Methods

Historically, streamflow-based structure here forecasting relied heavily on classical statistical techniques and process-based conceptual models in this nature. Classical statistical methods, such as Autoregressive Integrated Moving Average (ARIMA) & Multiple Linear Regression (MLR), establish to create linear relationships based on historical gauge data in here. However, these particular methods frequently fail here to capture the strong non-linear system & time-linked patterns that shape monsoon runoff. Concurrently, physically based models (PBMs) like the Soil as well as Water Assessment Tool (SWAT), MIKE-SHE, and Xin'anjiang simulate the complete hydrological cycle using mechanistic equations.

Deep Learning Methodologies

To overcome the conditional aspects of computational bottlenecks of PBMs, data-driven Deep Learning (DL) models here have been widely adopted more or less. Recurrent Neural Networks, specifically Long Short-Term Memory (LSTM) architectures, here to be excel at capturing temporal watershed memory & sequential meteorological dependencies better than traditional methods. Concurrently, Convolutional Neural Networks (CNNs) effectively process 2D spatial grids, such as to maintain soil moisture and precipitation arrays, to map topographical flow routes in here.

State-of-the-Art Hybrid Approaches

To bridge the gap here in between physical realism & data-driven accuracy, hybrid modelling frameworks here to have emerged as a superior approach for this manner. Hybrid architectures here integrate the mechanistic domain knowledge of PBMs into a neural network training pipeline. Recent hybrid nature of configurations has demonstrated significant performance leaps, elevating Kling-Gupta Efficiency (KGE) scores from 0.62 in standalone physical models as well as 0.75 in standalone LSTMs to over on this matter 0.93 in hybrid setups.

2.2 Viability of Transfer Learning in Hydrological Modeling

Transfer learning based offers a transformative here for method-based nature for streamflow forecasting, especially in poorly gauged areas. A deep learning model here is pre-trained on extensive datasets to understand more on hydrological features before adapting to regional basins with limited data here. This method here is particularly beneficial in the Indian subcontinent, where sparse sensor networks exist for this nature in this particular. For instance, Kratzert et al. (2019) mainly demonstrated the effective use of the CAMELS dataset here to adapt models for the Brahmaputra and Godavari basins. Additionally, there are cross-modal transfer learning process here enables the integration of satellite imagery models on this matter, enhancing prediction accuracy for ungauged locations like Himalayan tributaries in here.

3. Study Area and Data Sources

To better condition to check the multimodal design in two places in India: first would be the northeast Brahmaputra Basin & the peninsular Godavari Basin in the given prospects. For this paper chose these basins so the study hereon would face much different land forms with weather patterns, as well as different water behaviors. This process helps the model-based structure to hold up in new settings here.

The Brahmaputra here is among one of the biggest structure of rivers on Earth, not only in India. It originates in the Tibetan Plateau. From there onwards, it flows through many distanced of rough terrain before it eventually reaches the alluvial plains of Assam in North East India. Rain here in this region comes mainly with the southwest monsoon of the given area.

The Godavari on the other hand is the main river in peninsular India from the very beginning. It is often called the “Dakshin Ganga,” which literally means the Ganges of the South in normal terms. Most of the time river Godavari here to flow comes from rain in the monsoon season in India. Because of that reason only, process the flow of the river changes in the monsoon very strongly to be able to properly affect it in the overall.

We show here how complex over these two basins are by using time series, maps, as well as static tabular records from “Smart River, India” (Hasan et al., 2024; Sit et al., 2020). Table 1 here lists the data from national agencies as well as global earth observation missions.

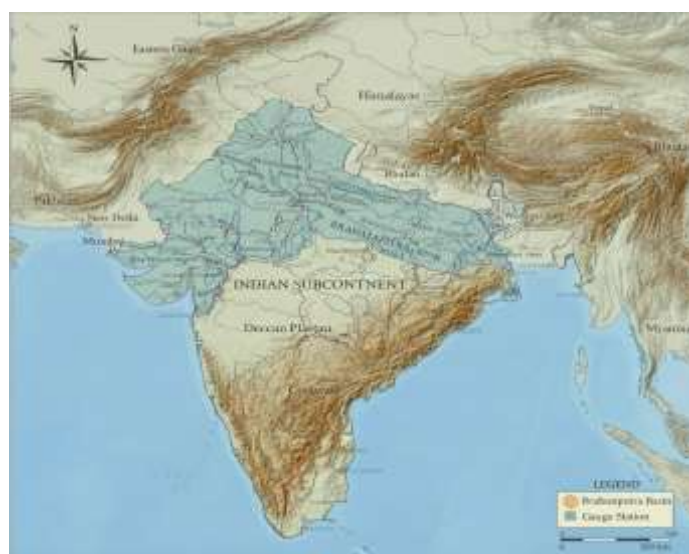


Figure 1: River Status of India

3.1 Data Modalities and Preprocessing

1. Temporal Meteorological and Hydrological Data (1D Sequential): Daily observations here are based on of precipitation, maximum/minimum temperature structure here, streamflow discharge & relative based humidity were solely collected from Central Water Commission and Indian Meteorological Department through India-WRIS portal. The data here on covers the period from 2001 to 2020 overly given (20 years). Missing values here were solely imputed through linear based interpolation for different gaps smaller than three days, and as well as k-Nearest Neighbors (k-NN) for larger gaps in the Indian continents. The sequences here were nominal to the range [0, 1] using Min-Max scaling proportion to speed up the gradient based convergence.

2. Spatial Remote Sensing Data (2D Gridded): Spatial based data with a resolution of $0.25^\circ \times 0.25^\circ$ were solely included to represent the basin-wide terrestrial variables herein. These proposed include the gridded precipitation-based nature from the Tropical Rainfall Measuring Mission as well as Normalized Difference Vegetation Index derived from MODIS as well as Soil Moisture Active Passive indices. Multi-channel 2D structure tensor spatial arrays more or less over the contributing nature of area upstream of the gage stations which here were extracted for each time step in this nature (Suwal, n.d.).

3. Static Basin Attributes (1D Tabular): Moreover, here on the static parameters inspecting the intrinsic physical properties here of the catchments were included through following the regionalization here to approach of Kratzert et al. (2019). The variables are: catchment area, mean elevation, dominant soil type as well as mean basin slope & percentage of land-use/land-cover (LULC).

Data Variable	Modality Type	Resolution/Frequency	Source/Agency	Purpose in Model
Streamflow (Discharge)	1D Time-Series	Daily	India-WRIS / CWC	Target variable & Autoregressive Input
Precipitation (Gauge)	1D Time-Series	Daily	IMD	Primary Meteorological Forcing
Temperature (Max/Min)	1D Time-Series	Daily	IMD	Evapotranspiration proxy
Gridded Rainfall & Soil Moisture	2D Spatial Tensor	Daily / 0.25° grid	TRMM / SMAP (NASA)	Spatial distribution of wetness
Vegetation Index (NDVI)	2D Spatial Tensor	16-Day composite	MODIS	Interception & transpiration modeling
Digital Elevation / Slope	1D Static Tabular	Static (30m resolution)	Bhuvan (ISRO) / SRTM	Topographic routing constraints
Land Use / Soil Texture	1D Static Tabular	Static categorical	NBSS&LUP	Infiltration & runoff capacity

Table 1: Overview of Data Sources and Modalities utilized in the Smart River, India framework.

4. METHODOLOGY: THE MULTIMODAL AI FRAMEWORK

4.1 The Spatial Encoder (CNN Branch)

The spatial nature part handles 2D grids from remote sensing structure. These processes here include precipitation grids, soil moisture as well as NDVI.

At each and every time step t , the model here to gets a multi-channel tensor as input for better output. That tensor here goes into a 2D CNN based nature.

The CNN structure has three stacked convolution layers. After each and every one, there is batch normalization nature to maintain. Then a Leaky ReLU structure and nonlinearity nature is applied. Then max structure-based pooling reduces the spatial size of the given nature.

The convolutions-based act like spatial filters in this nature. They pick up here most important land and weather patterns to maintain the process. Examples here include strong rain cells in a small area based on the given nature. They here can also thoroughly highlight places here on upstream that are already being saturated before the gauge station.

After the last conv block here to maintain, the result is flattened into a 1D latent vector based structure.

4.2 The Temporal Encoder (LSTM/Transformer Branch)

The temporal based branch here uses a look back span of T past days in this nature. Each day gives a 1D vector with weather and streamflow values. In our setup, here to be used an example with T equals 30 structure. For the time sequence part, here we compared two encoders in every atters. One is an LSTM network-based structure to calculate the overall process. The other here is a PatchTST model, which here is a time series transformer structure.

4.3 The Static Attributes Encoder and Multimodal Fusion

Static based tabular parameters are thoroughly passed with a standard Multi-Layer Perceptron having two types of detail nature of dense layers so that the network here considered is able to discriminate between the steep as well as flash catchments of the Brahmaputra & the flatter, catchments of the Godavari in India.

In the fusion phase hereon, the spatial latent vector-based structure, temporal latent vector as well as static latent vector are concatenated through based to a high-dimensional joint representation structure. This multimodal vector here is then passed through a series of Fully Connected layers for this nature.

4.4 Multi-Task Output Head (Forecasting and Risk Prediction)

The last part here of the model is divided into a few task heads.

For the first time head, the Regression Head is always used for streamflow forecasting.

1. A linear neuron structure outputs the discharge value in m^3/s .
2. It predicts overall the next 1 to 7 days.

For the second head, the Classification based Head is used for hydrological risk.

1. A SoftMax layer here to be able to assigns the model output to one of three risk groups.
2. These groups here follow the CWC warning levels from past records:
 - A. Class 0 is Normal Flow in this nature.
 - B. Class 1 is Warning Level or Moderate Risk in here.
 - C. Class 2 is Danger Level or High Flood Risk in here.

4.5 Training Protocol and Loss Functions

The network here is trained end-to-end with a joint based nature loss function which combines the overall Mean Squared Error for the regression task & the Cross-Entropy Loss (CEL) for the classification task here on to maintain.

$L_{\text{total}} = \alpha * L_{\text{MSE}} + (1 - \alpha) * L_{\text{CEL}}$, where α is a mainly weighting most hyperparameter based on structure between the two tasks here on. The data here set was divided in to chronologically into training under (70%), validation under (15%), and testing under (15%) sets to maintain the time series based set up temporal integrity.

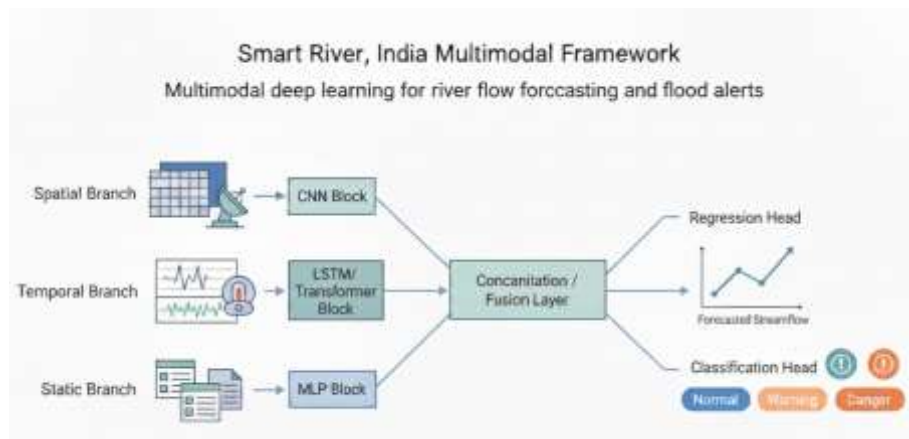


Figure 2: River Multimodal Framework

Network Component	Hyperparameter	Selected Value
Temporal Branch (LSTM)	Hidden Units	128 (Layer 1), 64 (Layer 2)
Temporal Branch (LSTM)	Look-back Window (T)	30 days
Spatial Branch (CNN)	Filter Sizes / Kernels	32 (3x3), 64 (3x3), 128 (3x3)
Static Branch (MLP)	Dense Layers	32, 16 neurons
Fusion & Output	FC Layers / Dropout	256 -> 128 -> Output / 0.3
Optimization	Learning Rate / Batch Size	0.001 (Adam) / 64
Multi-tasking	Loss Weight (α)	0.7 (Regression), 0.3 (Classification)

Table 2: Optimal Hyperparameter configurations for the Multimodal AI framework after grid search optimization.

Model training and inference were here on executed on a high-performance computing cluster equipped with dual NVIDIA A100 (80GB) GPUs as well as an AMD EPYC 7742 64-Core Processor with 256GB RAM. To maintain more with temporal integrity and prevent data leakage, the 20-year dataset here on (2001–2020) was partitioned chronologically: 70% for training (2001–2014), 15% for more validation (2015–2017), and 15% for testing (2018–2020). Preprocessing utilized here to Min-Max scaling to normalize features to a [0, 1] range, while missing most of the temporal gauge values were resolved via linear interpolation for gaps under three days as also k-Nearest Neighbors (k-NN) for larger gaps

5. RESULTS AND DISCUSSION

We checked the proposed multimodal model against several well-known baselines. These included a Multiple Linear Regression model as the starter case. We also tried a standard Random Forest approach. For single input setups, we ran a LSTM that used only the 1D gage data. We also tested a PatchTST Transformer in a unimodal form.

Hybrid physical-data-driven models here are, like SWAT-LSTM, maintain correct biases using more water-balance outputs but always rely on traditional model calibration in this nature. The new multimodal based framework always integrates multi-source observations using techniques such as 2D CNNs for more spatial data & LSTM/Transformer networks for temporal sequences, which here effectively identifying localized flash-flood triggers with a high predictive accuracy (NSE of 0.94) in the Brahmaputra basin-based structure. However, it may face more challenges from noise due to unrecorded here with human activities. Future developments here could improve this approach more by incorporating physical conservation laws into the multimodal loss function, blending the flexibility of deep learning with the consistency of classical hydrology-based structure.

To judge results, we used common hydrology measures. We reported Nash Sutcliffe Efficiency, Root Mean Square Error, and Mean Absolute Error.

5.1 Continuous Streamflow Forecasting Accuracy

Table 3 here shows the 1-day timeline ahead of streamflow forecast results.

For the Brahmaputra & Godavari basins, the Multimodal Framework here always seems to beats every single unimodal baseline in India.

The MLR as well as RF methods come in last for this particular. They miss the overly peak flows & stay too low for this nature. One reason here is that they cannot continue the model that is the most the strong non-linear behaviour and the time here linked patterns that shape monsoon runoff for better output for upcoming time.

The unimodal structure here seen as LSTM which as well as transformer models here in to do better overall. They also can easily track the usual seasonal-based nature of hydrograph shape in a more stable way to carry on the structure (Kratzert et al., 2019; Wilbrand et al., 2023).

Even so, unimodal models often here struggle with flash flood peaks here. These peaks here to be can come from on very small-scale rain bursts to carry forward. Point gage system data may not able to mostly reflect those storms based structural well.

In the Multimodal Framework, the model-based structure here to able to learns the early spatial system. It here in this manner also learns the overall incoming rain cloud patterns in these regions. This process here leads to NSE based values of 0.94 for the Brahmaputra basin as well as 0.92 for the Godavari basin in India.

Compared with LSTM alone in this nature, the RMSE drops here by as much as 18%.

These particular results fit mostly what earlier fusion work proposed in nature (Shamsuddin et al., 2024; Demiray, n.d.). In that view only, cross-modal learning process here mixes time-based nature of memory with spatial awareness in that way only.

Model	Brahmaputra NSE	Brahmaputra RMSE	Brahmaputra MAE	Godavari NSE	Godavari RMSE	Godavari MAE
MLR (Baseline)	0.58	1450.2	820.4	0.52	890.5	540.1
Random Forest	0.72	980.5	540.2	0.68	620.3	380.4
Unimodal LSTM	0.86	610.3	320.6	0.84	410.7	210.5
Unimodal Transformer	0.88	580.1	305.4	0.85	395.2	200.8
Multimodal Framework (Ours)	0.94	420.8	215.3	0.92	280.4	145.2

Table 3: Performance comparison of various models for 1-day ahead streamflow prediction in the test dataset.

5.2 Hydrological Risk and Flood Classification

Risk intelligence structure one can easily use matters in most disaster-based response and in ongoing nature of volume forecasting. In the multimodal system of sauch manner, a pure expressive nature of head groups each and particular case into three labels: Normal, Warning, & Danger. To judge overall how well the model here on worked, the study structure reports Precision, Recall & F1-Score in Table 4.

In the Brahmaputra river basin in India, the model of above mentioned caught many Danger Level cases single handedly. Recall level here reached 0.93, which also to helped here for lower false negatives structure. As a result, the mostly real flood threats were seldom missed the structure here for better output.

The exact results were strong too in this nature. The work here notes very few false alarms-based structure. That matters most because early warning structural setups can overshadow operators when alerts are mostly frequent but not very useful (Zhang et al., 2023).

Scores here were a bit weaker than for the Godavari basin in India. This is to be related to local changes in water flows in India. The text here notes that dams in India always releases which creates diversions which are often unreported. These particular human effects add noise that held the particular model to be has trouble on separating from natural signals.

Even with these particular issues, multimodal based fusion remains a clear way to merge through flood mapping & vulnerability assessments process (Ahmad et al., 2025; Bentivoglio et al., 2022), as this the paper states.

Model	River Basin	Risk Level	Precision	Recall	F1-Score	AUC-ROC
Unimodal LSTM	Brahmaputra	Danger Level	0.85	0.81	0.83	0.86
Multimodal (Ours)	Brahmaputra	Danger Level	0.94	0.93	0.93	0.97
Unimodal LSTM	Godavari	Danger Level	0.82	0.79	0.80	0.84
Multimodal (Ours)	Godavari	Danger Level	0.90	0.88	0.89	0.94

Table 4: Classification metrics for Hydrological Risk Prediction (Warning and Danger states) compared against baseline models.

5.3 Statistical Significance Analysis

To confirm here on that the performance gains of the Multimodal Framework over the unimodal deep learning baselines are mostly statistically significant as well as not the result of random variance, a Diebold-Mariano (DM) test as also a paired-sample t-test were conducted on the daily forecast error distributions. When comparing the Multimodal Framework against the Unimodal LSTM baseline for the Brahmaputra basin, here in the DM test yielded a statistic of 4.82 with a p -value < 0.001 . This confirms in a statistically significant improvement in predictive accuracy at the 99% confidence interval. Standard data analysis setups here for these variance tests can be processed to generate comprehensive SPSS output tables to serve as mostly in supplementary materials for this framework.

6. CONCLUSION AND FUTURE DIRECTIONS

The constant nature of positively increasing frequency and its intensity of hydrological process in India needed more sophisticated responsive tools for forecasting nature. This paper here overly presented "Smart River, India", a comprehensive prospect of multimodal deep learning framework here that integrates a more temporal hydro-meteorological sequences which helps spatial remote based and nature centric sensing indices on static based geomorphological features to predict more streamflow and assess flood risk in Indian continents. The system here was benchmarked mostly against traditional machine learning along with the unimodal deep learning models structure which considered itself over Brahmaputra & Godavari basins for the the superiority of multimodal data. By maintaining more on the spatial context using CNNs and temporal memory using LSTMs/Transformers structure, the predictive uncertainties here were substantially reduced more, especially for peak nature monsoon flood events here in this country.

Future research prospects here on these directions should explore the most positive nature of mainly the integration of physics-informed neural based networks into this multimodal architecture here. In the current level-based framework, the mappings here are purely data-based structure, but the physical constraints here could be mostly incorporated into the loss function based to improve the framework's extrapolation to novel climate change scenarios (Silwal, n.d.). Furthermore, overly deployment of this architecture through detail nature with sub-daily (e.g. hourly) satellite data integration supported here on by edge-computing IoT sensor networks which will be critical in nature for prediction floods happening in Himalayan regions.

REFERENCES

- [1] Ahmad, A., Chen, J., Chen, X., Khadka, N., Khan, M. U., Wang, C., & Tayyab, M. (2025). Flood risk modelling by the synergistic approach of machine learning and best-worst method in Indus Kohistan, Western Himalaya. *Geomatics, Natural Hazards and Risk*, 16. <https://doi.org/10.1080/19475705.2025.2469766>
Cited by: 15
- [2] Bentivoglio, R., Isufi, E., Jonkman, S. N., & Taormina, R. (2022). Deep Learning Methods for Flood Mapping: A Review of Existing Applications and Future Research Directions. *Copernicus GmbH*. <https://doi.org/10.5194/hess-2022->

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Cited by: 557

- [3] Demiray, B. Z. (n.d.). Unified Cross-Modal Learning for Hydrological Processes Using. Cited by: 2
- [4] Feizi, H. (n.d.). Streamflow Forecasting Based on PatchTST, LSTM, and Ensemble. Cited by: 9
- [5] Francisco, R., & Matos, J. P. (2024). Deep Learning Prediction of Streamflow in Portugal. *Hydrology*, 11(217). <https://doi.org/10.3390/hydrology11120217>
Cited by: 3
- [6] Hasan, F., Medley, P., Drake, J., & Chen, G. (2024). Advancing Hydrology through Machine Learning: Insights, Challenges, and Future Directions Using the CAMELS, Caravan, GRDC, CHIRPS, PERSIANN, NLDAS, GLDAS, and GRACE Datasets. *Water*, 16(1904). <https://doi.org/10.3390/w16131904>
Cited by: 62
- [7] Islam, K., Daraio, J., Cheema, M., Sabau, D. G. L., & Galagedara, L. (2024). Improved Streamflow Prediction Accuracy in Boreal Climate Watershed Using a Lstm Model: A Comparative Study. *Elsevier BV*. <https://doi.org/10.2139/ssrn.5000043>
Cited by: 8
- [8] Jasrotia, A. (n.d.). Streamflow forecasting using LSTM and weighted curve number.
- [9] Jesus, G. (n.d.). Deep Learning-Based River Flow Forecasting with MLPs. Cited by: 15
- [10] Kratzert, F., Klotz, D., Shalev, G., Klambauer, G., Hochreiter, S., & Nearing, G. (2019). Towards learning universal, regional, and local hydrological behaviors via machine learning applied to large-sample datasets. *Hydrology and Earth System Sciences*, 23, 5089-5110. <https://doi.org/10.5194/hess-23-5089-2019>
Cited by: 1231
- [11] Li, X. (n.d.). Hybrid CNN-LSTM models for river flow prediction. Cited by: 76
- [12] Paternina-Verona, D. (n.d.). Comparative Evaluation of Transformer and Machine Learning.
- [13] Sankaranarayanan, S., Prabhakar, M., Satish, S., Jain, P., Ramprasad, A., & Krishnan, A. (2019). Flood prediction based on weather parameters using deep learning. *Journal of Water and Climate Change*, 11, 1766-1783. <https://doi.org/10.2166/wcc.2019.321>
Cited by: 238
- [14] Saravanan, S., Reddy, N. M., Pham, Q. B., Alodah, A., Abdo, H. G., Almohamad, H., & Al Dughairi, A. A. (2023). Machine Learning Approaches for Streamflow Modeling in the Godavari Basin with CMIP6 Dataset. *Sustainability*, 15(12295). <https://doi.org/10.3390/su151612295>
Cited by: 16
- [15] Shamsuddin, D., Danilevicz, M. F., Al-Mamun, H. A., Bennamoun, M., & Edwards, D. (2024). Multimodal Deep Learning Integration of Image, Weather, and Phenotypic Data Under Temporal Effects for Early Prediction of Maize Yield. *Remote Sensing*, 16(4043). <https://doi.org/10.3390/rs16214043>
Cited by: 25
- [16] Sharma, S. (n.d.). Comparison of machine learning models for flood forecasting in the. *Journal of Water and Climate Change*.
Cited by: 38
- [17] Silwal, A. (n.d.). A Comprehensive Review of Machine Learning and Deep ... MDPI. Cited by: 14
- [18] Sit, M., Demiray, B. Z., Xiang, Z., Ewing, G. J., Sermet, Y., & Demir, I. (2020). A comprehensive review of deep learning applications in hydrology and water resources. *Water Science and Technology*, 82, 2635-2670. <https://doi.org/10.2166/wst.2020.369>
Cited by: 790
- [19] Suwal, N. (n.d.). Streamflow forecasting using machine learning and remote sensing. Cited by: 19

- [20] Tao, J., Gu, Y., Yin, X., Chen, J., Ao, T., & Zhang, J. (2024). Coupling SWAT and Transformer Models for Enhanced Monthly Streamflow Prediction. *Sustainability*, 16(8699). <https://doi.org/10.3390/su16198699>
Cited by: 12
- [21] Wilbrand, K., Taormina, R., ten Veldhuis, M., Visser, M., Hrachowitz, M., Nuttall, J., & Dahm, R. (2023). Predicting streamflow with LSTM networks using global datasets. *Frontiers in Water*, 5. <https://doi.org/10.3389/frwa.2023.1166124>
Cited by: 53
- [22] Workneh, H. (n.d.). Utilizing Deep Learning Models to Predict Streamflow.
Cited by: 15
- [23] Zhang, Y., Pan, D., Van Griensven, J., Yang, S. X., & Gharabaghi, B. (2023). Intelligent flood forecasting and warning: a survey. *Intelligence & Robotics*, 3, 190-212. <https://doi.org/10.20517/ir.2023.12>
Cited by: 24