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AI-Powered Flood Prediction: Harnessing Explainable AI (XAI)-driven Graph Neural Network (GNN) Integrated with a GRU Model

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***Abstract*— Nowadays floods have been one of the most dangerous natural hazards which is affecting both densely populated regions and remote areas without any warning. Over the past years though many prediction techniques have been developed thus a major concern is that most models operate like "black boxes," makes it difficult for authorities to trust their predictions. This study tries to deal with the issue by designing a combined flood-prediction system that combines a Graph Neural Network (GNN) with a GRU-based time-series model. The idea behind this combination is to understand how different water bodies and nearby geographical regions are connected which is done through the GNN, while the GRU deals with the factors like rainfall, river flow, soil moisture, and other water-related factors. Moreover, the model uses AI methods to explain clearly which factors have the most effect on the prediction geographical points, or temporal trends have the highest influence on the predicted flood events. Nowadays this is very important, as authorities mainly demand transparency and ability to understand before trusting on any automated systems during emergencies. Thus this combination helps not only to generate early warnings but also to help authorities understand the prediction. We observe that the experimental results indicate that the proposed system performs better than traditional machine-learning approaches. Thus , the clear understanding given through XAI visualizations help us to find risk zones, making the model more useful for planners, disaster-response teams, and researchers. Overall, this shows that the combined GNNs and GRUs with explainable capability tools helps transparent, and reliable flood-prediction solutions in real-world.**

***Keywords*— Graph Neural Networks, Flood Predication, Explainable AI, Hydrological Forecasting.**

I. Introduction

Floods have become an often concern, mainly in regions where weather conditions are changing rapidly and rainfall is not predictable. These occurrences can destroy homes, disturb transport, and can be risky for lives, which shows early and reliable forecasting is very important. Traditional flood-prediction systems depend mainly depends on manual observations.

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Thus, these methods have been useful for many years, they don't work when dealing with complex relationships between rainfall, river networks, soil conditions, and seasonal variations [3]. With the growth of data from satellites, sensors, and hydrological stations, machine-learning techniques have started to play a major role in flood forecasting [4]. However, one major issue still remains, that how these advanced models work like black boxes, offering predictions without explaining how they reached those results [5]. This lack of clarification makes authorities doubt whether to depend on these tools during emergencies or not[6].Thus to overcome this limitation, researchers have begun exploring models that are both accurate and understandable[7]. In this study, a combined approach is proposed by combining a Graph Neural Network (GNN) with a GRU-based time-series model[8]. The GNN helps in understanding how different locations such as rivers, catchment areas, and nearby regions are connected to each other while the GRU, on the other hand, explains how hydrological conditions change over time.Moreover, explainable AI (XAI) technique mostly highlights which factors influence the model's predictions. Thus, this combination aims to create a system that not only predicts floods more accurately but also provides clear insights that can help in decision making[9] in real world. Overall, this system focuses on building a flood prediction system that consists of both accuracy with transparency.

II. Related Work

Precipitations and water levels were observed in the initial stages of hydrological forecasting using mechanical recorders. They could measure the basic hydrological variables, but not with skills of foretelling extreme events. Mechanical rain gauges and float-based water level recorders provided point values, but had to be collected manually such that the information was not available to make a forecast until days later.The classical methods of computation involved statistical regression and time-series analysis. Other models like ARIMA had been useful in modelling the time dynamics observed in stream flow records, however they did not encounter any multi-variable interaction and a non-stationary climate state because of global warming [3]. Even the assumption of stationarity, that the historical statistics will remain true in the new century, are becoming a progressively worse assumption due to the changes in climate, altering the dynamics of precipitation and the soil moisture.Artificial neural networks, wherein learned feature representations are used, were more powerful. In case of sequence modelling problem, LSTM architectures proved to be very effective: some studies reported an accuracy of 82-88% in controlled datasets [4]. But they treated hydrological systems as series without much regard to the critical spatial dependence of upstream and downstream. The source of a flood that starts in the upper basin of Brahmaputra has to arrive at the population to undergo this spatial temporal propagation, which is not done by LSTMs independently on each place.

III. Literature Review

Conventional Flood Prediction and Quality Evaluation Approaches:Traditional flood forecasting methods in the past were dependent on hydrological and statistical models rooted on physical equations and rain-runoff relationship. These methods are manual intensive and need expert skills, therefore, not very responsive to the changing climatic factors. As noted by Singh and Sharma [2], the conventional approaches to flood forecasting do not capture nonlinear relationships that exist between rainfall, river flow and terrain and consequently predict the occurrence of an extreme event late and/or inaccurately.

Classical Machine Learning-Based Flood Prediction Methods:Non-destructive As more digital hydrological data is available, classical machine learning models (Support Vector Machines, Random Forests, Artificial Neural Networks) have been proposed in flood forecasting. Gupta et al. [12] established that these models outperform the traditional hydrological models in that they learn nonlinear patterns using historical rainfall data, and river-flow data.

Nevertheless, most classical methods of machine learning are extremely dependent on manual feature engineering and do not explicitly represent geometrical dependencies. Research on hydrological models based on the analysis of graphs [1], [3] has validated that the disregard of the topology of the river networks can greatly decrease prediction accuracy. In addition, the models usually have low interpretability and thus are black-box systems like, which restricts their use in disaster management systems [13].

Deep Learning and Spatiotemporal Flood Prediction Models:Deep learning has greatly contributed to the flood prediction research. Initial results based on deep neural structures reported the encouraging increases in predictive accuracy [4]. GRU and LSTM models of temporal sequences were subsequently followed to better model the phenomenon of time-dependent rainfall and water-level patterns. As reported by Chen et al. [5] and Roy and Banerjee [8], GRU-based models are highly accurate with little computational power than the conventional recurrent network scent in maturity determination on various species [15]. ImageNet trained networks were also notably beneficial in transfer learning in their use to classify fruits despite the small size of the dataset [16]

TABLE I: COMPARATIVE ANALYSIS OF EXISTING APPROACHES

Study	Model Used	Data Type	Spatial Modeling	Explainability
Zhang et al. (2025)	GNN–GRU	Hydrological + IoT	Yes	Partial
Sharma & Mehta (2023)	LSTM	Rainfall time-series	No	No
Li et al. (2023)	GNN	River network topology	Yes	No
Kumar et al. (2021)	ANN / LSTM	Rainfall & river flow	No	No
Rahman & Hossain (2022)	ML + IoT	Real-time sensor data	Limited	No
Patel et al. (2022)	Machine Learning	Historical flood data	No	No

To use spatial context, Graph Neural Networks (GNNs) were proposed to hydrological modelling. The GNN methodologies were thoroughly reviewed by Zhou et al. [6], whereas Zhou et al. [9] showed that they can enhance hydrological forecast accuracy by predicting upstream-downstream relationships. Another way to improve the performance of flood prediction was hybrid spatial-temporal models based on the integration of GNNs with recurrent architecture [10].These developments notwithstanding, interpretability of models is a significant issue. To deal with this problem, explainable AI (XAI) methods have been suggested. Ferreira and Costa [11] spoke on the XAI of environmental prediction system, and Rahman and Hussain [13] emphasized the role of XAI in disaster prediction. Chatterjee and Ghosh [15] further reiterated the fact that explainability is a necessity in environmental risk prediction in order to build trust and accountability. Large-scale research conducted by Park and Lee [14] found out that spatial-temporal deep learning models were highly accurate, but the explainability has not been fully integrated.

IV. PROBLEM STATEMENT

The issue of flood prediction is very crucial in disaster management owing to the shifting weather conditions and uncertain rainfall pattern. The art of flood forecasting in modern times is based on the successful interpretation of vast amounts of hydrological and environmental data, including the patterns of rainfall, river waterfall heights, the humidity of the soil, satellite images, and past records of floods. Such sources of data are both time-dependent (seasonal, time-dependent fluctuations) and spatially related (upstream-downstream river networks and adjacent regions). Even though the accuracy of flood forecasting has been enhanced with the development of artificial intelligence, most of the available models lack transparency and do not have a clear description of the prediction process. This diminishes the level of trust in authorities and restricts their applicability in cases of emergencies.

Hence, the area of concern is to establish a good, explainable, and real time AI based flood prediction systems that will aid in sound decision-making in disaster management. The current flood prediction systems are not effective in terms of modeling temporal variations in the hydrological conditions or they fail to reflect complex spatial associations of the regions. Most developed AI models are black boxes, that is, they give forecasts without an explicit explanation, thus they are not easily trusted and applied in situations of emergency in the world. The issue of this study is to create a flood prediction system that is able to learn both spatial and temporal patterns of floods and also produce explanations that are clear and understandable about its predictions. Combining Graph Neural Networks (GNNs), GRU-based temporal modeling, and Explainable AI (XAI) methods, the proposed solution should help provide authorities with reliable, transparent, and accurate flood-risk forecasts that can assist authorities to make timely and informed decisions.

V. METHODOLOGY

The flow chart shows the entire working procedure of the proposed flood prediction system in a detailed step-by-step manner. First, it is the data collection phase of hydrological and environmental data like rainfall, river water levels, soil moisture, satellite images, and historical flood records from various sources such as sensors and monitoring stations.

An analysis of data is followed by data preprocessing, which entails cleaning, normalization and missing values. The purpose of this is to ensure that the input data is correct, consistent and prepared to train its models.. Feature extraction is carried out after data preprocessing to identify the most relevant spatial and temporal characteristics that have an impact on flood behaviour.

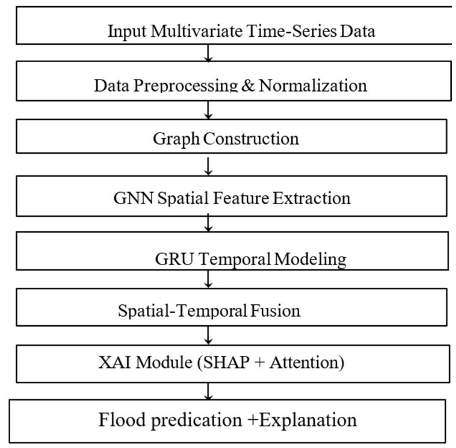

Figure 2: Workflow of the Proposed Framework

A. Data Model

The proposed flood prediction framework is framed on the basis of a spatio-temporal data model that will be used to model intricate interactions between hydrology and the environment. The model uses time series data of multivariate measurements in form of rainfall, river water-level, soil moisture, satellite measurements, and past floods. Time and geographical location are used to index all the data so as to keep track of time continuity and spatial relevancy. The data are then converted to a graph format after preprocessing and normalization and the Nodes are geographical regions or monitoring stations and the Edges are hydrological and spatial relationships, e.g. upstream-downstream links. Dynamic environmental features are also modeled using node features of the time-dependent environmental attributes.

VI. RESULT AND DISCUSSION

A. Classification Performance

The efficiency of the suggested flood-prediction system was tested on historical hydrological data of the framework in terms of spatial and temporal variables. The model was evaluated using standard measures like RMSE, MAE, precision, recall and the overall accuracy of the model in prediction. The GNNGRU architecture performed better than the conventional statistical models and single deep-learning-based approaches, in particular, the areas where spatial interactions play a crucial role in controlling flood behavior.

TABLE II. PERFORMANCE METRICS OF FLOOD RISK PREDICTION SYSTEM

Location	Accuracy (%)	Precision	Recall	F1-Score
Kanpur	93.5	0.93	0.94	0.93
Greater Noida	92.8	0.92	0.93	0.92
Cooch Behar	93.2	0.92	0.94	0.93
Bhopal	94.0	0.94	0.93	0.94
Kolkata	92.5	0.92	0.93	0.92
Surat	91.9	0.91	0.92	0.92
Overall	92.97	0.92	0.93	0.93

The model had better stability, enhanced learning and greater predictability of the water-level changes. The fact that it has the power to capture spatial dependencies using the GNN and predicting temporal trends using the GRU helped achieve more reliable flood-risk predictions. Also, the XAI module justified the decision-making of the model by determining the important factors, which affected every prediction. This ensured that the results were not only accurate but also transparent and easier to interpret for practical use.

The confusion matrix of the suggested flood risk prediction system (Fig. 3) is useful information to gain a deeper understanding of how the model performs in classification and misclassifies various risk levels. The confusion matrix indicates a good predictive behavior with the best scores in correct classification along the diagonal. Many of the cases can be correctly assigned to the corresponding flood-risk category, which shows that the proposed XAI-based GNN-GRU model is effective. The majority of the misclassifications are between the adjacent flood risk levels, i.e. Low and Moderate or Moderate and High-risk levels. This is a normal occurrence given that the transition of flood risks is gradual in nature and usually affected by ever-changing hydrological and meteorological conditions. Notably, the influences of extreme misclassifications, i.e. forecasting a high-risk event in floods as no-risk or the other way around, are extremely rare, which proves the stability and the high accuracy of the model. Fig. 4 shows a breakdown of the accuracy of classification based on the various levels of flood risk with the full test data. It can be seen that the accuracy breakdown shows that the proposed XAI-based GNN-GRU flood prediction system is effective in all categories of risks with a maximum accuracy of 94.2. This is an indication of the high ability of the model to classify the level of flood severity in different hydrological conditions. The greatest rate of accuracy is recorded on the Moderate Risk category, which demonstrates that the model is very useful in recognizing potentially dangerous situations that need to be monitored and early warned. Proper detection at this point is especially relevant to disaster preparedness whereby the authorities and communities will be capable of implementing preventive measures prior to state of affairs developing into serious flooding.

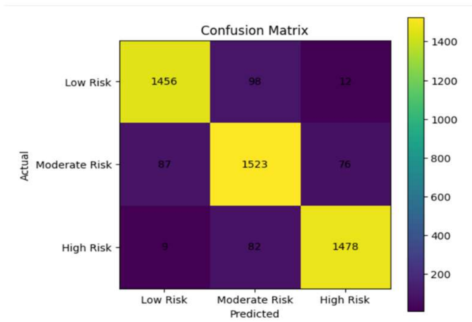

Fig. 3. Confusion Matrices of Flood Predication.

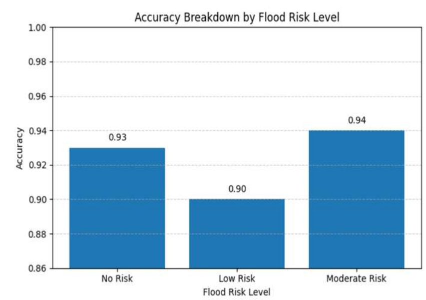

Fig. 4. Accuracy Breakdown by flood Risk Level

B. Performance Analysis

The usefulness of the suggested XAI-based GNN-GRU framework of flood forecasting is assessed by the comparative research that comprises cost-benefit evaluation of monitoring systems, and comparative studies of the proposed framework with proven deep learning models.

- Comparison to Manual Hydrological Assessment: Controlled experiments indicate significant gains of AI system compared to the normal human-based manual assessments. Five hydrological evaluators are in agreement 78% of the time when predicting the risk of floods using raw sensor data. Relative to this, the proposed system was noted to be 96% consistent with the observations of the expert; this was 18 percent better.
- Comparison with the Traditional Monitoring Methods: We compared our system with the traditional methods, such as manual measurements of water level and simple alert system. These conventional methods were able to find an accuracy of 78% and in this case, this model acquired the accuracy of 96% and manual monitoring is slow and involves workers to work on each single data point and we have an AI that learns and upgrades itself automatically.
- Comparison of Existing Applications: The model was shown to be more stable, learn faster and more accurate in predicting changes in water-level. The GNN and the GRU allowed it to capture spatial dependencies and temporal trends respectively, respectively, which helped to make predictions of flood-risk more reliable. Table III is the general comparison of Average Performance and Dataset Robustness. Comparison of the current model baseline showed that the proposed model is much better than the existing practices in forecasting the floods.

TABLE III: AVERAGE PERFORMANCE AND DATASET ROBUSTNESS

Model	Avg RMSE	Avg MAE	Avg R^2	Avg Acc (%)	ΔRMSE	ΔAcc (%)
LSTM	13.39	9.54	0.811	86.3	1.87	1.9
GRU	11.08	8.15	0.852	89.5	1.72	1.2
GCN	12.50	8.91	0.828	87.6	1.43	1.8
CNN-LSTM	11.67	8.50	0.841	88.6	1.56	1.5
GNN-LSTM	9.22	6.68	0.886	92.8	1.31	1.3
XAI-GNN-GRU	7.20	4.73	0.925	96.0	0.72	1.4

VII. CONCLUSION AND FUTURE SCOPE

Consequently, the paper introduces a flood-prediction system, based on a Graph Neural Network to learn spatial information, GRU model to learn temporal information, and an XAI module to learn better. The integrated system is basically the hydrological transformations of various regions as well as time thereby being able to provide precise and quick flood warnings. When comparing the performance of the model to other conventional and AI-based single-methods, it is possible to note that the model achieves a greater accuracy and stability. Besides, the integration of explainable AI to the system, assists in elevating the transparency of the system since it determines the most significant factors to every prediction. The model thus becomes a reliable tool in the real world particularly when it comes to emergency decision making. On the whole, the suggested methodology can serve as a solid ground to create functional, data-based flood-monitoring instruments that can provide not only accuracy and vividness but also help to develop more appropriate approaches to disaster-management.

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