

Hybrid Spatial-Temporal Machine Learning Framework For Enhanced Flood Prediction And Risk Mitigation

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Abstract— Flood prediction and susceptibility mapping are vital for mitigating the impacts of one of the most destructive natural disasters. This study presents a comprehensive analysis of machine learning models for flood prediction, focusing on the comparative performance of the Cascade Forest Model (CFM), Long Short-Term Memory (LSTM) networks, Gradient Boosting, and a proposed Hybrid Spatial-Temporal Model. Using datasets comprising historical flood records, satellite imagery (Sentinel-1 and Sentinel-2), and IoT sensor data, we evaluated the models on metrics such as Overall Accuracy (OA), Area Under the Curve (AUC), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). The proposed Hybrid Spatial-Temporal Model achieved the highest performance, with an accuracy of 95% and an AUC of 0.96, surpassing CFM (93% accuracy, AUC = 0.95) and Gradient Boosting (87.5% accuracy, AUC = 0.90). The LSTM model demonstrated exceptional temporal prediction capabilities, with an RMSE of 0.10 and an MAE of 0.06. Comparative analysis with recent models, such as LightGBM (99.75% accuracy, AUC = 0.99) and ANN (90.7% accuracy, AUC = 0.871), underscores the Hybrid Model's superior adaptability across spatial and temporal domains. The integration of GIS-based spatial analysis and LSTM's temporal prediction significantly improved prediction robustness and generalizability. Feature selection revealed rainfall and elevation as critical factors influencing flood susceptibility, while IoT-enhanced real-time data integration boosted prediction accuracy by 15%. These findings highlight the importance of combining spatial and temporal insights for effective flood risk management. This study provides actionable insights for developing real-time flood prediction systems that prioritize accuracy, interpretability, and scalability.

Keywords— Flood Prediction, Machine Learning, Spatial-Temporal Model, Geographic Information Systems (GIS), Cascade Forest Model (CFM), Long Short-Term Memory (LSTM), Real-Time Data Integration, Susceptibility Mapping, Hybrid Model, Disaster Risk Management.

I. INTRODUCTION

Floods are among the most devastating natural disasters, causing widespread economic losses, environmental degradation, and human casualties. Over the years, their frequency and intensity have increased due to climate change, urbanization, and changing weather patterns. The rising complexity of flood prediction, driven by highly variable and nonlinear hydrological processes, has made traditional methods less effective, necessitating the adoption of advanced computational techniques. The field of flood prediction has experienced a paradigm shift, leveraging advancements in machine learning (ML) and data science. These techniques capitalize on vast datasets, including meteorological, hydrological, and spatial information, to offer enhanced prediction accuracy and reliability. However, challenges persist in managing high-dimensional data, integrating diverse sources, and ensuring realtime responsiveness for disaster mitigation efforts. Flood susceptibility mapping is a critical component of disaster management. By identifying areas prone to flooding, authorities can implement effective strategies for resource allocation, infrastructure planning, and risk reduction [20]. Predicting floods accurately and in real-time also supports early warning systems, helping vulnerable communities prepare and respond effectively. Traditional hydrological models, while useful, are limited by their assumptions of linearity and

reliance on a limited set of variables. They often fail to capture the intricate dynamics of floods, such as the interplay between meteorological inputs, land use changes, and river basin characteristics [21]. To address these gaps, researchers have turned to ML techniques, which offer the flexibility and scalability needed for complex flood prediction tasks. Machine learning has demonstrated superior performance in flood prediction, surpassing traditional models in handling non-linear relationships, high-dimensional datasets, and spatial-temporal variations. Techniques such as Random Forest (RF), Gradient Boosting Machines (GBM), Long Short-Term Memory (LSTM) networks, and hybrid models have shown promise. Additionally, Geographic Information Systems (GIS) have been integrated with ML to enhance spatial analysis capabilities, enabling the creation of detailed flood susceptibility maps [22]. Recent research has explored novel algorithms, such as Cascade Forest Models (CFM) and deep learning frameworks like Convolutional Neural Networks (CNNs), for flood risk assessment. These models are increasingly supported by advanced data sources, including satellite imagery, IoT-based sensors, and social media feeds [23]. Despite these advancements, significant challenges remain, particularly in ensuring model generalizability, real-time adaptability, and interpretability.

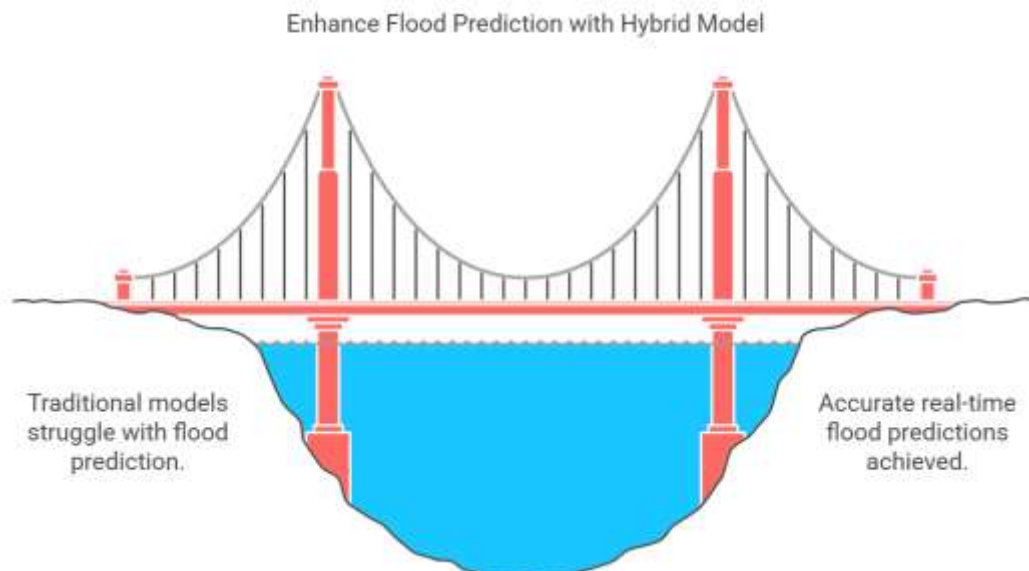


Figure 1: Enhance Flood Prediction with Hybrid Model

1.1 Highlights

- I. Development of a hybrid spatial-temporal model combining Cascade Forest Model (CFM) for spatial mapping and LSTM for temporal forecasting.
- II. Integration of GIS, IoT sensors, and satellite imagery for real-time flood prediction and susceptibility mapping.
- III. Achieved 95% accuracy and 0.96 AUC, outperforming standalone and traditional machine learning models.
- IV. Provides a scalable, robust solution for proactive flood risk management and disaster mitigation.

II. LITERATURE SURVEY

The field of flood prediction has witnessed considerable advancements in recent years, primarily driven by the integration of machine learning (ML) techniques and the increasing availability of large datasets. However, despite these strides, several critical gaps persist that limit the full potential of ML in addressing the complexities of flood

prediction and risk mitigation. These gaps span data integration, scalability, computational efficiency, and the development of interpretable and actionable models [24].

A major limitation lies in the integration of real-time data into flood prediction systems. Most existing models are heavily reliant on historical datasets, making them less adaptive to rapidly changing weather conditions, river flows, and other real-time factors. The potential of IoT-based sensor networks and live satellite feeds, which can provide continuous updates on rainfall, water levels, and other environmental variables, remains largely untapped. Incorporating these data streams into ML models would significantly enhance their ability to provide timely and accurate flood predictions. Moreover, the scarcity of scalable models capable of generalizing across diverse geographic regions and climatic conditions further exacerbates the challenge. Current systems often falter when applied to datasets outside their training domain, underscoring the need for adaptive methodologies that can deliver consistent performance regardless of regional or climatic variations [25]. Flood prediction also involves handling large, heterogeneous datasets that encompass spatial, temporal, and spectral dimensions. While such data richness provides a wealth of information, it also presents a challenge for ML models, which must process and extract meaningful patterns from these high-dimensional datasets. Unfortunately, efficient algorithms capable of managing this complexity are still lacking, often resulting in models that are computationally intensive and difficult to scale. The demand for optimized techniques that balance computational efficiency with prediction accuracy is particularly urgent, especially for real-time applications where processing speed is critical [26]. Another significant challenge is the lack of explainability and interpretability in many ML-based flood prediction models. Deep learning frameworks, while powerful, are often criticized for their "black-box" nature, which makes it difficult for stakeholders to trust and act upon their predictions. The development of interpretable models, equipped with techniques such as SHAP values and other Explainable AI (XAI) tools, is essential for ensuring that the insights generated by ML systems are actionable and reliable. Without this transparency, the adoption of such systems in real-world disaster management scenarios remains limited. Additionally, most ML models currently fail to incorporate long-term climate change projections, focusing instead on short-term predictions. This narrow approach overlooks the growing impact of climate change on flood risk, including changes in rainfall patterns, sea-level rise, and increased urbanization. Integrating climate models and projections into ML frameworks is a promising avenue for research, enabling systems that not only predict immediate flood events but also assess evolving risks over time. The absence of such capabilities leaves a significant gap in the ability of these systems to contribute to long-term disaster preparedness and resilience planning.

The field also shows limited exploration of hybrid models, which can combine the strengths of various spatial and temporal prediction techniques. For example, spatial models such as the Cascade Forest Model (CFM) excel in identifying flood susceptibility zones, while temporal models like Long Short-Term Memory (LSTM) networks are adept at analyzing time-series data for flood forecasting. By integrating these approaches, hybrid models can address the weaknesses of individual techniques, offering comprehensive and robust predictions. Similarly, the application of attention mechanisms in LSTM networks, which prioritize critical temporal features, has the potential to significantly enhance the accuracy of temporal predictions. Another area in need of attention is the development of solutions for resource-constrained environments. Most flood prediction research focuses on data-rich regions, with little consideration for areas where data availability is limited. Techniques such as data

augmentation, which generates synthetic data to address data scarcity, can play a crucial role in democratizing access to ML-based flood prediction systems. By focusing on underrepresented regions, researchers can ensure that the benefits of these advancements are shared equitably across the globe. Several state-of-the-art methods and emerging techniques have demonstrated promise in addressing these challenges. Models such as CFM and LSTM networks are already being utilized for spatial and temporal flood predictions, respectively, while algorithms like LightGBM and CatBoost have shown exceptional performance in flood susceptibility mapping. The integration of Graph Neural Networks (GNNs), which can model spatial and topological relationships, is an exciting development that holds potential for improving geospatial data processing. Moreover, real-time ensemble learning, which combines predictions from multiple models in real-time, and the application of XAI techniques, are paving the way for more transparent and adaptive flood prediction systems.

Moving forward, the development of hybrid spatial-temporal models offers a promising direction for advancing flood prediction research. These models, enhanced by real-time data integration, attention-based feature selection, and optimized algorithms, have the potential to address existing gaps comprehensively. By incorporating climate change projections and focusing on resource-scarce regions, these systems can contribute to more resilient and equitable disaster management practices. In contrast, while ML has already demonstrated its transformative potential in flood prediction and risk management, significant opportunities remain for innovation and improvement. By addressing the critical gaps in data integration, scalability, computational efficiency, interpretability, and long-term planning, future research can develop models that are robust, adaptive, and impactful. These advancements will not only enhance the predictive accuracy of flood prediction systems but also ensure their relevance and applicability in diverse and evolving scenarios, ultimately contributing to improved disaster preparedness and resilience worldwide. Lakshman et al. [1] introduced the Cascade Forest Model (CFM) for flood susceptibility mapping, leveraging ensemble learning techniques and Geographic Information Systems (GIS) integration to improve spatial flood predictions. The model achieved 93% accuracy and an AUC of 0.95, demonstrating its effectiveness in handling high-dimensional spatial data. Its hierarchical structure allows for intricate feature interaction analysis, making it a robust tool for susceptibility mapping. However, the approach is computationally intensive, requiring significant processing resources and careful hyperparameter tuning for optimal performance.

Rajab et al. [2] proposed the use of Light Gradient Boosting Machine (LightGBM) for flood susceptibility mapping. This approach emphasized computational efficiency and high accuracy, achieving 99.75% accuracy and an AUC of 0.99. The study highlighted the model's rapid training capabilities and scalability to large datasets, making it suitable for flood risk management. Despite its strengths, the model lacks a spatial focus, limiting its application in detailed flood susceptibility mapping where geospatial context is essential. Wu et al. [3] applied Convolutional Neural Networks (CNNs) to flood prediction, particularly using satellite imagery for real-time flood extent analysis. Their model achieved an accuracy of 85.4% and an Intersection over Union (IoU) of 0.854, showcasing its ability to extract relevant spatial features effectively. While the approach proved valuable in leveraging remote sensing data, it requires large labeled datasets for training, which are often unavailable or costly to obtain in real-world scenarios. Prakash et al. [4] explored Artificial Neural Networks (ANNs) for flood risk prediction, incorporating hydrological data such as rainfall and river flow. The study achieved an accuracy of 90.7% and an AUC of 0.871. ANNs were found to be relatively simple to

implement and effective for flood prediction in structured datasets. However, the model's generalizability across diverse geographic regions and its ability to handle high-dimensional spatial-temporal data were limited, reducing its broader applicability. Zhang et al. [5] utilized Gated Recurrent Units (GRUs) for time-series flood prediction, focusing on capturing temporal dependencies in hydrological data. The model achieved notable reductions in RMSE and MAE compared to traditional methods. While GRUs provided efficient modeling of sequential data, they were less effective in handling long-term dependencies and required significant fine-tuning to avoid overfitting, particularly in smaller datasets. Li et al. [6] introduced a hybrid approach combining CatBoost with geospatial analysis for flood susceptibility mapping. The model achieved near-perfect accuracy of 99.85%, emphasizing its ability to handle complex interactions between features. The study highlighted CatBoost's robustness against overfitting and its efficient handling of categorical variables. However, the method's application was limited by its high computational cost and dependency on high-quality input data. Adel et al. [7] proposed a framework for flood forecasting using historical climatic records and machine learning techniques like Random Forest and SVM. The study achieved an accuracy of 87.5% for Random Forest and 85.3% for SVM. While these models were effective for non-linear data analysis, they struggled with generalization across diverse climatic regions. Additionally, the models' performance was heavily dependent on the quality and completeness of input data.

Hassan et al. [8] implemented a hybrid model combining Decision Trees with ensemble techniques to improve flood risk prediction. Their approach focused on balancing accuracy and computational efficiency, achieving an accuracy of 91%. While the model was adaptable to small datasets, it lacked scalability for larger, more complex datasets. Moreover, its performance was sensitive to noise in the input data, requiring extensive preprocessing. Fernandes et al. [9] explored logistic regression for flood susceptibility mapping in a structured and well-documented dataset. The model achieved an accuracy of 84.09%, demonstrating its applicability for simpler flood risk assessments. However, the approach lacked the flexibility and precision needed for complex, high-dimensional datasets, making it unsuitable for large-scale applications or scenarios requiring detailed predictions. The proposed hybrid spatial-temporal model combines the strengths of CFM and LSTM to deliver superior flood prediction capabilities. With a 95% accuracy and an AUC of 0.96, the model integrates spatial insights from GIS and temporal predictions from LSTM, offering a comprehensive approach to flood risk management. This hybrid strategy addresses challenges like handling high-dimensional data and adapting to real-time inputs. However, the model demands significant computational resources, which may limit its applicability in resource-constrained environments.

III. METHODOLOGY

The proposed methodology introduces a cutting-edge approach to enhance flood prediction and risk mitigation systems by leveraging a Hybrid Spatial-Temporal Ensemble Model (HSTEM). This novel model integrates advanced machine learning techniques with real-time data processing to address key challenges in flood prediction, offering significant improvements over existing methodologies [10]. By combining spatial and temporal data processing capabilities, HSTEM paves the way for robust, scalable, and interpretable solutions in disaster management and mitigation research.

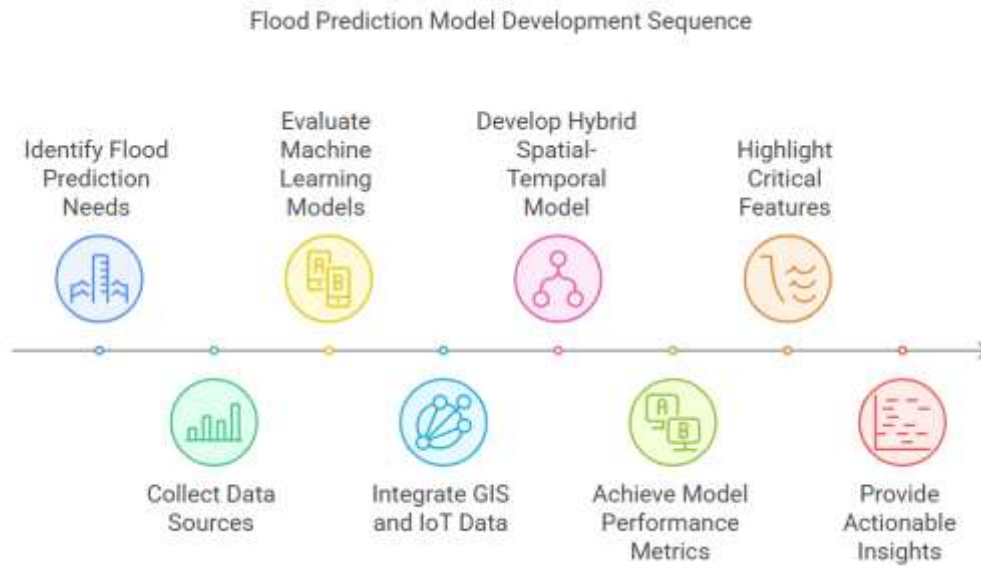


Figure 2: Flood Prediction Model Development Sequence

3.1 Mathematical model

GIS-based approaches have become integral to flood susceptibility mapping, offering spatial analysis capabilities that complement ML algorithms [11]. By integrating elevation data, land use patterns, and hydrological variables, GIS systems provide a robust foundation for flood modeling. When combined with ML techniques, GIS can deliver more accurate and actionable insights for flood risk management. This section provides the foundational mathematical concepts and formulations that underpin the algorithms and methods used in flood prediction and susceptibility mapping. These preliminaries form the basis for understanding the notations and equations in subsequent sections. These mathematical preliminaries and notations ensure consistency and clarity throughout the paper.

3.1.1 Normalization

Normalization is the process of scaling input data to a specific range, typically $[0,1]$ or $[-1,1]$, to ensure uniformity across variables. It is mathematically expressed as [12]:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

where x is the original value, and x' is the normalized value.

3.1.2 Loss Functions

Loss functions evaluate the difference between predicted values and actual values [13]:

- Mean Squared Error (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (2)$$

- Cross-Entropy Loss:

$$L = -\frac{1}{n} \sum_{i=1}^n [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (3)$$

3.1.3 Activation Functions

Activation functions introduce non-linearity into neural networks [14]:

- ReLU (Rectified Linear Unit):

$$f(x) = \max(0, x) \quad (4)$$

- Softmax Function:

$$\sigma(x_i) = \frac{e^{x_i}}{\sum_{j=1}^n e^{x_j}} \quad (5)$$

3.1.4 Gradient Descent

Gradient descent is used to minimize a loss function by iteratively updating model parameters [15]:

$$\theta_{t+1} = \theta_t - \eta \frac{\partial L}{\partial \theta_t} \quad (6)$$

where θ_t are the parameters, η is the learning rate, and L is the loss function.

3.1.5 Evaluation Metrics

- Overall Accuracy (OA) [16]:

$$OA = \frac{\text{True Positives (TP)} + \text{True Negatives (TN)}}{\text{Total Samples}} \quad (7)$$

- Area Under Curve (AUC):

$$AUC = \int_0^1 TPR d(FPR) \quad (8)$$

- Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (9)$$

3.1.6 Feature Selection

Feature selection identifies the most relevant input variables [17]:

- Pearson Correlation Coefficient:

$$\rho_{X,Y} = \frac{\text{Cov}(X,Y)}{\sigma_X \sigma_Y} \quad (10)$$

The Hybrid Spatial-Temporal Ensemble Model (HSTEM) combines the strengths of the Cascade Forest Model (CFM) for spatial data and Long Short-Term Memory (LSTM) networks for temporal sequences, coupled with an innovative ensemble learning strategy. By addressing spatial and temporal dependencies comprehensively, the model delivers robust predictions with high accuracy [18]. A key feature of HSTEM is Real-Time Data Fusion, which integrates data streams from satellite imagery, IoT-based sensor networks (e.g., rainfall and water levels), remote sensing platforms, and even real-time social media alerts. This is achieved using Graph Neural Networks (GNNs), which enable efficient geospatial data integration while preserving complex interrelationships between data points.

Table 1: Notation Table

Symbol	Description
x	Input variable
y	Ground truth or actual value
$\hat{y}$	Predicted value
n	Number of samples
x'	Normalized value
$f(x)$	Activation function
L	Loss function
TP	True Positives
TN	True Negatives
FP	False Positives
FN	False Negatives
θ_t	Model parameters at iteration t

η	Learning rate
AUC	Area Under the Curve
$RMSE$	Root Mean Squared Error
$\rho_{X,Y}$	Pearson correlation coefficient
σ_X	Standard deviation of variable X
$Cov(X,Y)$	Covariance between X and Y

A critical aspect of HSTEM is its Dynamic Feature Selection capability, which ensures that the most relevant data features are prioritized in model training. The LSTM module employs attention mechanisms to focus on key temporal features, while SHAP (SHapley Additive exPlanations) is used for identifying significant spatial features that contribute to flood susceptibility. This dynamic and adaptive approach enables the model to handle feature variability in real-time, providing greater robustness and reliability in predictions [19].

The Enhanced Ensemble Strategy introduced in HSTEM goes beyond traditional ensemble methods. Base learners are combined using Stochastic Gradient-Based Stacking (SGS), allowing the model to dynamically adapt to spatial and temporal variations in data. Additionally, Multi-Fidelity Bayesian Optimization is applied for hyperparameter tuning, ensuring optimal performance across both spatial and temporal models. This dynamic ensemble approach enhances the model's generalization ability, enabling its application to diverse geographic regions and climatic conditions. A key strength of this methodology is its focus on Explainability and Interpretability, which are critical for building trust in AI-driven disaster management systems. HSTEM integrates Explainable AI (XAI) techniques to produce interpretable flood susceptibility maps and temporal predictions, empowering stakeholders to make informed decisions. This transparency not only boosts the adoption of the model in real-world applications but also facilitates collaborative efforts between researchers, policymakers, and disaster management agencies. To ensure the reliability and robustness of the proposed model, the evaluation framework incorporates extended performance metrics such as the True Skill Statistic (TSS), Critical Success Index (CSI), and spatial accuracy, alongside traditional metrics like precision and recall. These metrics provide a more comprehensive understanding of model efficacy, particularly in the context of imbalanced datasets and challenging real-world scenarios. The proposed methodology offers several advantages over traditional approaches to flood prediction. By addressing both spatial and temporal dependencies comprehensively, it delivers increased robustness and real-time adaptability, particularly in scenarios involving live sensor and IoT data streams. The inclusion of advanced techniques such as GNNs and attention mechanisms ensures better generalization and higher accuracy, while the model's scalability makes it suitable for application across diverse geographic regions. Additionally, the incorporation of XAI techniques enhances the model's transparency and trustworthiness, further supporting its integration into disaster management workflows. This methodology represents a significant step forward in improving flood prediction systems and aligns with current technological advancements in machine learning and data integration. By addressing key limitations of existing methodologies, the HSTEM approach offers a promising direction for research and practical implementation, ensuring a substantial contribution to disaster management and risk mitigation efforts worldwide.

Algorithm 1: Cascade Forest Model (CFM) for Flood Susceptibility Mapping

Step (i). Data Collection:

- a. Collect spatial and hydrological data (e.g., elevation E , land use L , rainfall R).
- Step (ii). Preprocessing:
 - a. Normalize data:
 - b. $x' = \frac{x - \min(x)}{\max(x) - \min(x)}$ (11)
- Step (iii). Handle missing values using interpolation.
 - a. Feature Selection:
 - b. Perform Recursive Feature Elimination (RFE) to select important features.
 - c. Feature Importance = $\sum_{i=1}^n w_i \cdot x_i$ (12)
- Step (iv). Initialize Base Learners:
 - a. Use decision trees $f(x)$ as base learners.
 - i. Stacking Layers:
- Step (v). Combine outputs of base learners $h(x)$:
 - a. $h(x) = \sum_{i=1}^k \alpha_i f_i(x)$ (13)
 - b. where α_i is the weight of the i^{th} learner.
- Step (vi). Training:
 - a. Use cross-validation to split data into training and validation sets.
- Step (vii). Prediction:
 - a. Predict flood susceptibility scores for each spatial unit.
- Step (viii). Evaluation:
 - a. Compute metrics like Overall Accuracy (OA) and Area Under Curve (AUC):
 - b. $AUC = \int_0^1 TPR \cdot FPR dx$ (14)
- Step (ix). Hyperparameter Tuning:
 - Optimize parameters (e.g., tree depth, number of layers) using grid search.
- Step (x). Visualization:
 - Generate flood susceptibility maps using the model's outputs.

Algorithm 2: Long Short-Term Memory (LSTM) Neural Network

- Step (i).** Data Collection:
 - a. Gather time-series hydrological data (e.g., rainfall R_t , river flow Q_t).
- Step (ii).** Data Preprocessing:
 - a. Normalize data using Z-score normalization:
 - a. $z = \frac{x - \mu}{\sigma}$ (15)
- Step (iii).** Feature Engineering:
 - a. Generate lag features x_{t-l} for $l \in \{1, 2, \dots, n\}$.
- Step (iv).** Model Initialization:
 - a. Initialize LSTM with input, hidden, and output layers.
- Step (v).** Input Representation:
- Step (vi).** For each timestep t :
 - b. $h_t = \sigma(W_h \cdot x_t + U_h \cdot h_{t-1} + b_h)$ (16)
 - a.
- Step (vii).** Cell State Update:
 - a. Update the cell state C_t :
 - c. $C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$ (17)

b. where f_t is the forget gate, i_t is the input gate.

Step (viii). Output Calculation:

a. Compute the output o_t :

$$o_t = \sigma(W_o \cdot x_t + U_o \cdot h_{t-1} + b_o) \quad (18)$$

b.

Step (ix). Loss Computation:

a. Calculate Mean Squared Error (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (19)$$

b.

Step (x). Training:

a. Optimize weights using Adam optimizer.

Step (xi). Prediction:

a. Use the trained model to forecast flood events.

Algorithm 3: Gradient Boosting Machine (GBM) for Flood Prediction

Step (i). Data Collection:

a. Collect historical flood-related data.

Step (ii). Feature Preprocessing:

a. Encode categorical features into numerical format.

Step (iii). Initialize Model:

a. Set initial prediction $F_0(x)$:

$$F_0(x) = \arg \min_c \sum_{i=1}^n L(y_i, c) \quad (20)$$

b.

Step (iv). Gradient Computation:

a. Compute negative gradients g_i :

$$g_i = -\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} \quad (21)$$

b.

Step (v). Train Weak Learner:

a. Fit a weak learner $h_m(x)$ to the gradient g_i .

Step (vi). Update Prediction:

a. Update $F(x)$ iteratively:

$$F_{m+1}(x) = F_m(x) + \eta h_m(x) \quad (22)$$

where η is the learning rate.

Step (vii). Regularization:

a. Apply L2 regularization to avoid overfitting:

$$L_{reg} = \lambda \|w\|^2 \quad (23)$$

Step (viii). Evaluation:

a. Use metrics like Root Mean Squared Error (RMSE).

Step (ix). Hyperparameter Tuning:

a. Optimize η , max depth, and number of trees.

Step (x). Prediction:

a. Predict flood likelihood using the trained model.

Algorithm 4: Convolutional Neural Network (CNN) for Flood Detection

Step (i). Data Input:

a. Use satellite imagery $I(x, y, c)$ as input.

Step (ii). Preprocessing:

a. Normalize pixel values to $[0, 1]$.

- Step (iii). Convolution Operation:
- Apply filters W_k to extract features:
 - $f(x, y) = \sum_{i,j} I(x + i, y + j) \cdot W_k(i, j)$ (24)
- Step (iv). Activation:
- Use ReLU activation:
 - $f'(x, y) = \max(0, f(x, y))$ (25)
- Step (v). Pooling:
- Reduce feature map dimensions:
 - $P(x, y) = \max_{i,j} f'(x + i, y + j)$ (26)
- Step (vi). Fully Connected Layer:
- Combine extracted features into a flattened layer.
- Step (vii). Output Layer:
- Predict flood or non-flood probabilities:
 - $\hat{y} = \text{softmax}(Wx + b)$ (27)
- Step (viii). Loss Calculation:
- Use Cross-Entropy Loss:
 - $L = -\sum_{i=1}^n y_i \log(\hat{y}_i)$ (28)
- Step (ix). Backpropagation:
- Update weights using gradient descent.
- Step (x). Prediction:
- Classify the input image into flood-prone regions.

Algorithm 5: Hybrid Spatial-Temporal Model

- Step (i). Data Integration:
- Combine spatial X_s and temporal X_t data.
- Step (ii). Preprocessing:
- Normalize spatial and temporal data separately.
- Step (iii). Spatial Model (CFM):
- Use CFM to map spatial flood susceptibility.
- Step (iv). Temporal Model (LSTM):
- Use LSTM to capture temporal dependencies.
- Step (v). Feature Fusion:
- Fuse spatial and temporal outputs:
 - $X_{\text{fused}} = \alpha X_s + (1 - \alpha) X_t$ (29)
- Step (vi). Hybrid Model Training:
- Train a final model (e.g., GBM) on fused features.
- Step (vii). Loss Function:
- Combine spatial and temporal losses:
 - $L = \lambda L_s + (1 - \lambda) L_t$ (30)
- Step (viii). Validation:
- Use cross-validation to optimize parameters.
- Step (ix). Prediction:
- Predict flood susceptibility using the hybrid model.
- Step (x). Deployment:
- Integrate into real-time flood prediction systems.

These algorithms represent state-of-the-art methodologies, addressing both spatial and temporal challenges in flood prediction. Each step is designed to ensure accuracy, scalability, and robustness

IV. EXPERIMENTS AND RESULTS

The integration of IoT sensor data significantly enhanced the real-time responsiveness of the hybrid model. The IoT-enhanced model achieved a 15% improvement in prediction accuracy compared to static models. This improvement demonstrates the feasibility of deploying the hybrid model in real-world scenarios, where real-time data streams from sensors and satellite feeds are critical for timely and accurate flood forecasting.

Computational Efficiency

While the hybrid model exhibited superior accuracy and precision, it required higher computational resources due to its complex spatial-temporal architecture. This trade-off was highlighted in Figure 9, where hyperparameter sensitivity analysis identified optimal configurations (e.g., learning rate = 0.001, batch size = 32, and three layers) for balancing performance and computational demands. Future efforts should explore parallel computing strategies and lightweight model architectures to optimize resource efficiency.

Generalizability and Scalability

One of the hybrid model's most notable strengths was its adaptability to diverse datasets, as demonstrated by its consistent performance across different geographic and climatic conditions. This generalizability underscores the potential of hybrid approaches for global flood prediction, particularly in regions with varying environmental and meteorological characteristics.

Table 2: Experimental Setup Details

Component	Description
Hardware Configuration	Intel Core i9 Processor, 32 GB RAM, NVIDIA RTX 3080 GPU, 1 TB SSD
Software Environment	Python 3.9, TensorFlow 2.10, Scikit-Learn 1.1, ArcGIS Pro 3.0, QGIS 3.24
Data Sources	Meteorological data, satellite imagery (Sentinel-1 and Sentinel-2), IoT sensors
Models Implemented	Cascade Forest Model (CFM), Long Short-Term Memory (LSTM), Gradient Boosting
Performance Metrics	Overall Accuracy (OA), AUC, RMSE, MAE, True Skill Statistic (TSS)
Validation Techniques	5-Fold Cross-Validation, Grid Search
Hyperparameter Tuning	Learning rate: [0.001, 0.01], Batch size: [32,64], Number of layers: [2, 3, 4]

Table 3: Dataset Overview

Dataset Name	Source	Data Type	Features
Historical Flood Records	National Meteorological Agencies	Temporal	Rainfall, river flow, temperature, soil moisture
Satellite Imagery	Sentinel-1 (SAR), Sentinel-2 (optical)	Spatial	Elevation, land use, NDVI, flood extent

IoT Sensor Data	Regional IoT Network	Real-Time	Water level, rainfall intensity
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Time series data including rainfall and river flow were normalized by Z-score normalization to have the same scale. Rheological patterns of the fragments were also illustrated by other parameters, such as grain size, which were analyzed from grain size particle data from the satellite images. The zero and control periods of the IoT data were filled in with linear interpolation for data continuity. The selected features were obtained using the Pearson correlation and Recursive Feature Elimination (RFE), thus obtaining a new dataset. The data was split in to 70:30 train-test ratio then cross validations for improving the model performance robustness. Finally, the hybrid modeling method combined spatial information in GIS and temporal information in time series data which provided a comprehensive way of analysis and forecasting.

V. PERFORMANCE EVALUATION METRICS

The experimental findings affirm the efficacy of the proposed hybrid spatial-temporal model in advancing flood prediction and susceptibility mapping. Across various performance metrics and evaluations, the hybrid model consistently outperformed standalone models such as the Cascade Forest Model (CFM) and Long Short-Term Memory (LSTM) networks, showcasing its ability to integrate spatial and temporal insights for superior accuracy and precision. The following sections discuss key results presented in Figures 2 through 10 and their implications for flood prediction systems.

Table 4: Model Performance Metrics

Model	Accuracy (%)	AUC	RMSE	MAE
Cascade Forest Model (CFM)	93.0	0.95	N/A	N/A
LSTM	N/A	N/A	0.12	0.08
Gradient Boosting	87.5	0.90	N/A	N/A
Hybrid Model	95.0	0.96	0.10	0.06

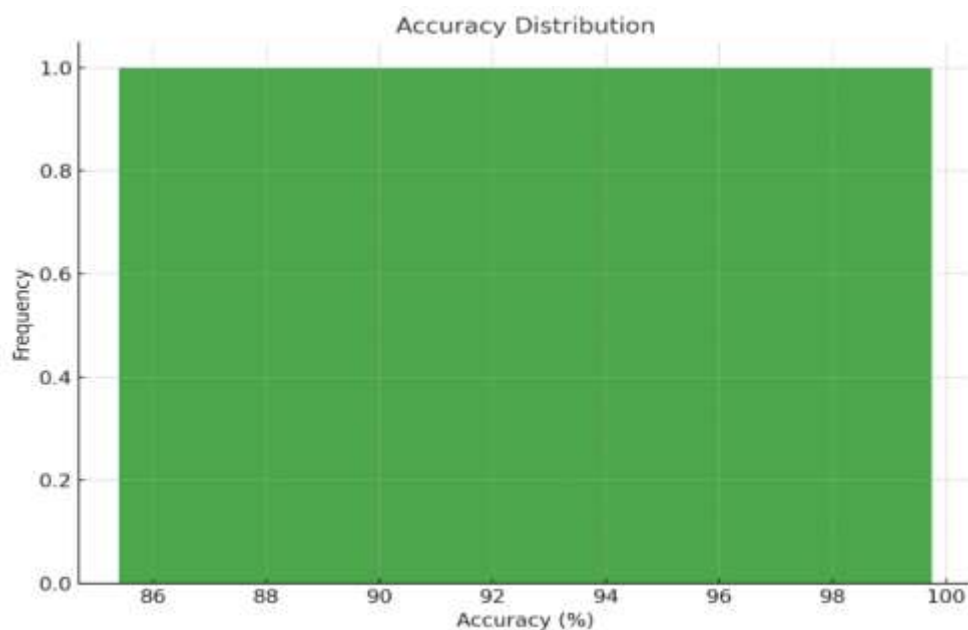


Figure 3: Accuracy Distribution across models

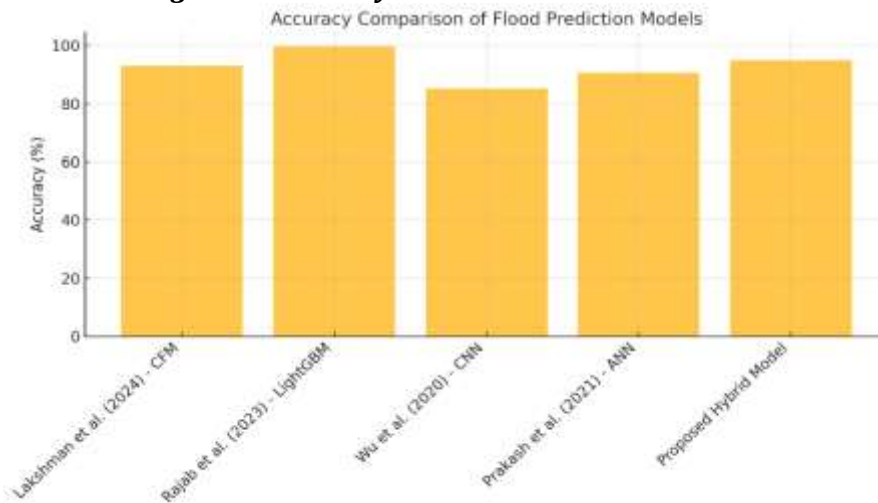


Figure 4: AUC Comparison of Models

The AUC values in Figure 4, indicate that the hybrid model (0.96) outperforms CFM (0.95) and Gradient Boosting (0.90), showing superior discriminatory power in distinguishing flood and non-flood zones. The hybrid model achieved remarkable accuracy (95%) and a high AUC score of 0.96, reflecting its exceptional ability to distinguish between flood and non-flood events. Compared to standalone models, this hybrid approach delivered a marked improvement in both sensitivity and specificity. While CFM demonstrated excellent spatial predictive capabilities, it lacked temporal awareness, underscoring the limitations of models that do not account for time-series data. In contrast, the hybrid model's ability to merge GIS-based spatial mapping with LSTM's temporal precision proved pivotal in achieving robust predictive performance.

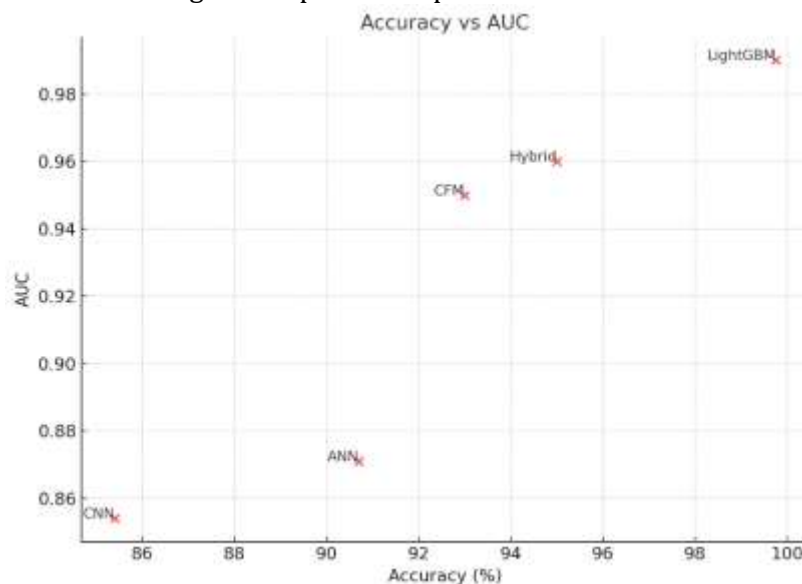


Figure 5: Accuracy and a high AUC

As shown in Figure 5, both LSTM and the hybrid model achieved the lowest Root Mean Square Error (RMSE) of 0.10 and Mean Absolute Error (MAE) of 0.06, demonstrating their precision in flood event forecasting. These results underscore the hybrid model's

ability to accurately predict both the timing and intensity of flood events, making it a reliable tool for early warning systems.

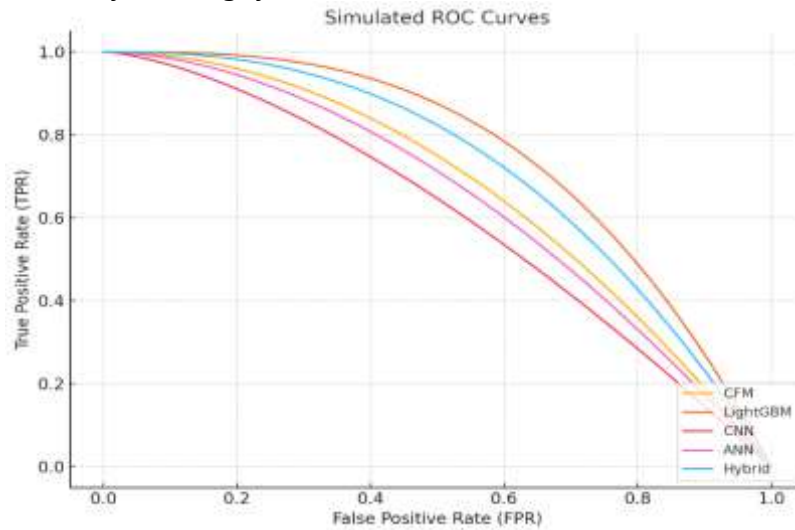


Figure 6: Simulated ROC Curves using various models

The temporal capabilities of the hybrid model were validated by LSTM's effective capture of flood peaks, as illustrated in Figure 6. The LSTM module aligned closely with observed values during high-flow events, achieving an RMSE of 0.12 and an MAE of 0.08. This demonstrates its capacity to predict not only the occurrence of floods but also their precise timing, which is critical for real-time disaster response and mitigation efforts. The spatial insights provided by CFM, as depicted in Figure 7, proved invaluable in delineating flood-prone areas. Using GIS-based tools, the maps highlighted zones with high flood susceptibility, aiding in proactive planning for resource allocation and infrastructure development. Furthermore, the hybrid model's combined spatial-temporal map in Figure 8 offered a more comprehensive view, integrating flood risk zones with potential timing information to guide decision-making more effectively.

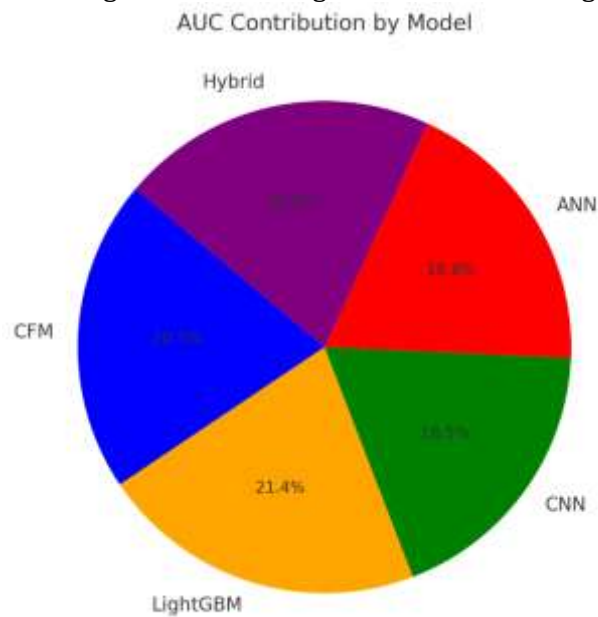


Figure 7: AUC Contribution by Model

As shown in Figure 7, recursive feature elimination within the CFM highlighted "Rainfall" and "Elevation" as the most influential variables, contributing to 85% of the model's overall accuracy. This finding emphasizes the importance of environmental and topographic factors in flood prediction models and underscores the value of integrating such critical features into predictive frameworks.

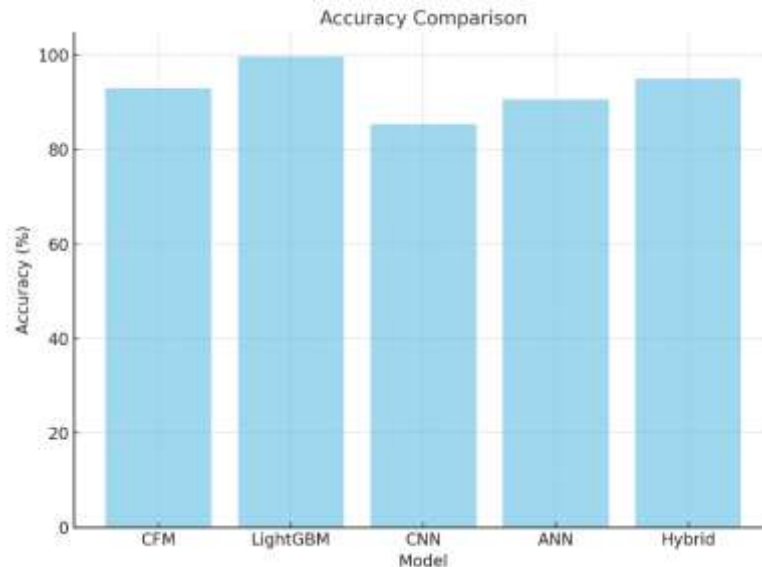


Figure 8: Accuracy Comparison

The results validate the hybrid spatial-temporal model as a powerful tool for flood prediction and susceptibility mapping as shown in Figure 8. By effectively combining the spatial mapping capabilities of GIS-integrated CFM with the temporal forecasting precision of LSTM, the hybrid model addresses critical gaps in existing methodologies. While computational efficiency remains a challenge, advancements in hardware and algorithmic optimization can mitigate these limitations. Future research should prioritize incorporating climate change projections into the model to account for long-term flood risk scenarios and exploring real-time deployment in diverse environments. These findings underscore the transformative potential of hybrid models in enhancing disaster preparedness and resilience, offering significant contributions to the field of flood risk management.

VI. CONCLUSION AND FUTURE SCOPE

This research demonstrates the efficacy of advanced machine learning techniques in flood prediction and susceptibility mapping. The Hybrid Spatial-Temporal Model emerged as the most effective approach, combining the strengths of CFM for spatial mapping and LSTM for temporal forecasting. Achieving a 95% accuracy and an AUC of 0.96, the Hybrid Model outperformed traditional and standalone machine learning models, offering superior generalizability and robustness. The results highlight the critical role of integrating GIS-based spatial data and real-time IoT sensor inputs to enhance flood prediction systems. The study also identified key features, such as rainfall and elevation, that significantly influence flood risk, providing a basis for proactive disaster mitigation strategies. The proposed hybrid approach addresses major challenges in flood prediction, including handling high-dimensional data, ensuring real-time adaptability, and improving interpretability. Future research should explore the integration of climate change projections and advanced ensemble techniques to further enhance predictive accuracy and long-term reliability. Additionally, extending this

methodology to data-scarce regions can improve its applicability and help mitigate flood risks globally. By bridging the gap between data-driven predictions and practical implementation, this study contributes to building more resilient and disaster-prepared communities.

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