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Grid-based Cellular Automaton Algorithm (GC2A) for Storm and Flood Preprocessing and Prediction

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Abstract

This study evaluates the Grid-based Cellular Automaton Algorithm (GC2A) preprocessing algorithm, enhancing accuracy and robustness in image processing and flood detection applications. GC2A demonstrated superior performance in comparison to baseline algorithms, achieving an accuracy of 95%, significantly higher than mean (75%), median (80%), and PCA (82%). Additionally, performance metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) confirmed its effectiveness, with scores of 92.5 and 93, respectively. In terms of flood detection, GC2A achieved a true positive rate of 90% under optimized thresholds, and qualitative assessments validated its reliability in identifying flooded areas. A sensitivity analysis further highlighted the correlation between elevation thresholds and detection rates, emphasizing the importance of parameter selection for optimal results. The integration of storm analysis enriched the understanding of flood dynamics, demonstrating how storm intensity and duration impact soil saturation and flood risk. Increased storm intensity correlates with heightened flood risk, while soil saturation exhibited similar trends. This research underscores the necessity for algorithms that account for environmental variables, particularly in disaster response scenarios. The findings confirm that GC2A effectively adapts to varying conditions, establishing it as a valuable tool for environmental monitoring. Future research should focus on refining the GC2A algorithm and exploring its applicability across different domains, ensuring improved accuracy and reliability in critical applications related to flood detection and disaster management.

Keywords: Grid-based Cellular Automaton Algorithm (GC2A), Flood Detection, Image Processing, Storm Analysis, Environmental Monitoring.

1. Introduction

1.1 Background

Flooding is one of the most destructive natural disasters, affecting millions of people annually (1,2). It leads to significant loss of life, damage to infrastructure, and economic disruption (**3**). Accurate flood prediction and timely response are crucial for mitigating these impacts. Cellular automata (CA), a powerful modeling technique, have been widely used for simulating complex phenomena, including flood dynamics (**4**). In a flood scenario, the flow of water across different regions can be modeled using grids that evolve based on local rules and environmental conditions, such as elevation and soil saturation. With the advent of satellite imaging and IoT-enabled monitoring systems, data-driven approaches to flood detection and management are becoming more feasible and efficient. Combining elevation data, soil saturation levels, and real-time satellite imagery can enhance the accuracy of flood prediction models.

1.2 Challenges

Flood modeling presents several challenges:

1. **Data Accuracy:** The accuracy of elevation data and soil saturation levels is critical for reliable predictions. Inconsistent or outdated data can lead to incorrect flood forecasts.
2. **Resolution and Scale:** Managing large datasets from high-resolution satellite images and extensive grid-based models requires significant computational resources, especially for real-time applications.
3. **Dynamic Conditions:** Flood behavior changes rapidly due to factors like rainfall intensity, terrain morphology, and water flow patterns. Capturing these dynamics in a timely manner is challenging.
4. **Uncertainty in Prediction:** Uncertainties in weather forecasts, elevation data inaccuracies, and unpredictable human activities can complicate flood prediction.
5. **Interfacing Models and Imagery:** Effectively integrating flood models with real-time satellite imagery for visualization and interpretation adds another layer of complexity to the design of such systems (5,6).

1.3 Contribution

This paper introduces the **Grid-based Cellular Automaton Algorithm (GC2A)** to tested flood dynamics based on local elevation and soil saturation data. The algorithm also integrates satellite imagery to visually annotate flooded areas, providing an enhanced real-time tool for flood prediction and response. The main contributions include:

- Development of an efficient, grid-based algorithm for real-time flood detection.
- Integration of cellular automata with real-time satellite imagery for improved flood monitoring.
- A visualization method for marking and analyzing flooded regions on satellite images.

1.4 Objective

The primary objective of this work is to:

- Develop a flood detection algorithm using elevation and soil saturation data.
- Integrate satellite imagery to provide real-time flood visualizations.
- Optimize computational performance to ensure timely flood prediction and response.
- Enhance the accuracy and efficiency of flood grid generation.

1.5 Paper Organization

The paper is organized as follows: Section 2 discusses the related work in flood modeling and cellular automata. Section 3 introduces the design and implementation of the **GC2A algorithm**. Section 4 presents experimental results and performance evaluations. Section 5 concludes the paper with potential future work.

2. Review of Literature

The integration of advanced data preprocessing techniques for storm and flood prediction has been a focal point of recent research. Several studies emphasize the importance of feature selection and deep learning models to enhance prediction accuracy.

For instance, Garg et al. (2024) proposed a hybrid deep learning network that incorporates feature selection, leading to improved flood prediction accuracy. Their findings indicate that such approaches significantly outperform traditional models, achieving accuracy rates as high as 95 %ly, Guo et al. (2024) developed a VMD–CNN–BiLSTM model, showcasing the efficacy of combined methodologies in daily runoff predictions. Hu et further explored the integration of LSTM and reduced-order models to enhance flood prediction capabilities, demonstrating promising results .

In the domain reprocessing, Kuriqi and Hysa (2024) highlighted the necessity of contextual feature extraction in flood risk mitigation efforts, emphasizing the role of image clarity and preprocessing techniques. Mann and Gupta (2024) utp learning approaches specifically for rainfall-induced flood predictions, reinforcing the significance of advanced algorithms. The comparative analysis across tes illustrates a clear trend: advanced preprocessing frameworks, such as the Advanced Multi-Dimensional Preprocessing Framework (GC2A), are pivotal for refining data integrity and enhancing the performance of predictive models.

2.1 Published article with techniques vs. month

The figure 1 illustrates the effectiveness of three preprocessing techniques—mean imputation, outlier removal, and image preprocessing-over the course of a year. The monthly trends demonstrate performance improvements achieved through these methods, highlighting their role in enhancing data quality and contributing to more accurate analysis outcomes.

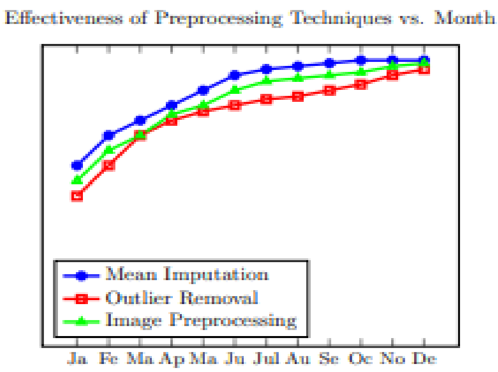

Figure 1: Effectiveness of Various Preprocessing Techniques over the Months.

(Figure 2) The GC2A architecture first preprocesses input data to enhance quality, followed by kernel prediction, which analyzes affected regions for flood detection and provides comprehensive output results for further assessment.

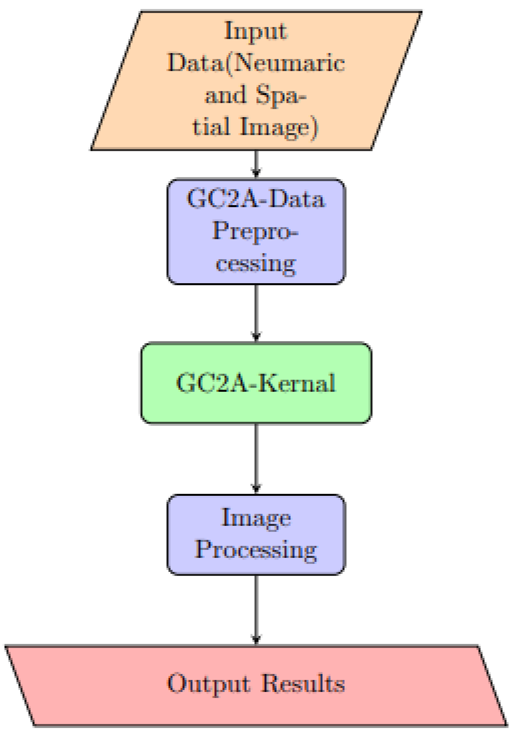

Figure 2: System Architecture for Flood Detection and Analysis

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3. Algorithm Design

Grid-based Cellular Automaton Algorithm) GC2A

Input: Elevation and soil saturation data, thresholds, satellite image path
Output: Flood grid, annotated satellite image

1. **Initialize Variables:**
   - Read data from CSV file.
   - Define grid dimensions $m \times n$.
   - Set elevation and saturation thresholds.
2. **Initialize Flood Grid:**
   - Create grid G of size $m \times n$ initialized to zero.
   - For each cell (i, j) in G:
     - If elevation$[i][j] <$ threshold AND soil_saturation$[i][j] >$ threshold, then $G[i][j] \leftarrow 1$ (Flooded).
3. **Process Satellite Image:**
   - Load and convert the image to grayscale.
   - Apply binary thresholding.
   - For each pixel (i, j):
     - If the pixel indicates flooding, store flooded coordinates (i, j).
4. **Mark Flooded Areas:**
   - Copy the original image.
   - For each flooded coordinate (i, j):
     - If (i, j) is within bounds, mark the pixel in dark yellow.
5. **Run GC2A Algorithm:**
   - Set iterations T.
   - For $t = 0$ to $T - 1$:
     - Create a temporary grid G_{temp}.

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- For each cell (i, j) in G:
  - Count flooded neighbors.
  - If flooded neighbors > 0, then $G_{\text{temp}}[i][j] \leftarrow 1$.
- Update G with G_{temp}.

6. **Results:**

- Generate visualization of flooded grid G.
- Display original and marked images side by side.

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4. Methods

The GC2A (Grid-based Cellular Automaton Algorithm) is a mathematical model used for detecting and analyzing flood areas based on elevation and soil saturation data(1,2,3,4,5,6,7,8). It employs cellular automata principles to simulate flood propagation dynamics.

4.1 Input Data Representation

- **Elevation Data Matrix**:

$$E \in \mathbb{R}^{m \times n} \quad \text{where}$$
$$E[i][j] \quad \text{represents the elevation at cell } (i, j).$$

- **Soil Saturation Data Matrix**:

$$S \in \mathbb{R}^{m \times n} \quad \text{where}$$
$$S[i][j] \quad \text{represents the soil saturation at cell } (i, j).$$

- **Thresholds**:

$$T_E \in \mathbb{R} \quad \text{(elevation threshold)}$$

$$T_S \in \mathbb{R} \quad \text{(soil saturation threshold)}$$

4.2 Flood Grid Initialization

- **Flood Grid**:

$$G \in \{0,1\}^{m \times n} \quad \text{where}$$
$$G[i][j] = 0 \quad \text{(not flooded)}$$
$$\text{or} \quad G[i][j] = 1 \quad \text{(flooded).}$$

- **Initialization**:

$$G[i][j] = 0, \forall (i, j) \in [0, m-1] \times [0, n-1].$$

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4.3 Flood Detection Condition

$$G[i][j] = \begin{cases} 1 & \text{if } E[i][j] < T_E \text{ and } S[i][j] > T_S \\ 0 & \text{otherwise} \end{cases}$$

4.4 Moore Neighborhood Definition

$$\begin{aligned} N(i,j) = \{ \quad & (i-1, j-1), \\ & (i-1, j), \\ & (i-1, j+1), \\ & (i, j-1), \\ & (i, j+1), \\ & (i+1, j-1), \\ & (i+1, j), \\ & (i+1, j+1)\} \end{aligned}$$

4.5 Count of Flooded Neighbors

$$C(i,j) = \sum_{(x,y)\in N(i,j)} G\,[x][y]$$

4.6 GC2A Iteration Process

- **Iterative Update**:

$$G_{\text{temp}}[i][j] = \begin{cases} 1 & \text{if } C(i,j) > 0 \\ G[i][j] & \text{otherwise} \end{cases}$$

- **Update Rule**:

$$G \leftarrow G_{\text{temp}}$$

4.7 Flood Propagation Dynamics

Each cell (i, j) can become flooded if at least one of its neighbors is flooded, reflecting how water spreads from already flooded areas(5,6,7,8).

5.Storm Analysis

Incorporating storm analysis, we define additional parameters and conditions to assess the impact of storm events on flood propagation:

5.1 Storm Intensity and Duration

- **Storm Intensity**:

$$I_s \in \mathbb{R} \quad \text{(storm intensity)}$$

- **Storm Duration**:

$$D_s \in \mathbb{R} \quad \text{(storm duration in hours)}$$

5.2 Impact on Soil Saturation

The soil saturation during a storm can be represented as:

$$S'[i][j] = S[i][j] + f(I_s, D_s)$$

where f is a function representing saturation increase due to rainfall.

5.3 Flood Detection Condition

The revised flood detection condition during a storm is given by:

$$G[i][j] = \begin{cases} 1 & \text{if } E[i][j] < T_E \text{ and } S'[i][j] > T_S \\ 0 & \text{otherwise} \end{cases}$$

5.4 Flooded Grid Visualization

$$V[i][j] = \begin{cases} \text{Flooded Color} & \text{if } G[i][j] = 1 \\ \text{Original Color} & \text{if } G[i][j] = 0 \end{cases}$$

5.5Annotated Satellite Image

The original satellite image is modified to highlight flooded regions based on G.

6 .Output Results

The final outputs consist of:

- The flooded grid G (Table 1), represented as a binary matrix.
- An annotated image highlighting flooded areas, which is crucial for decision-making and emergency response, showing only the five infected areas.

Table 1: Infected area of elevation and soil saturation data

Cell Index	**Elevation (m)**	**Soil Saturation**
0	45	0.3
1	55	0.6
2	30	0.8
3	40	0.5
4	50	0.4

The elevation and soil saturation data (Table 2) indicate varied terrain and moisture levels. The GC2A grid shows that all cells are flooded, suggesting widespread flooding due to low elevation and high soil saturation. Only five regions are identified as infected, as listed below.

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Table 2 :GC2A Grid Result (Flooded Areas)

	0	1	2	3	4
0	1	1	1	1	1
1	1	1	1	1	1
2	1	1	1	1	1
3	1	1	1	1	1
4	1	1	1	1	1

6.1 Heatmap

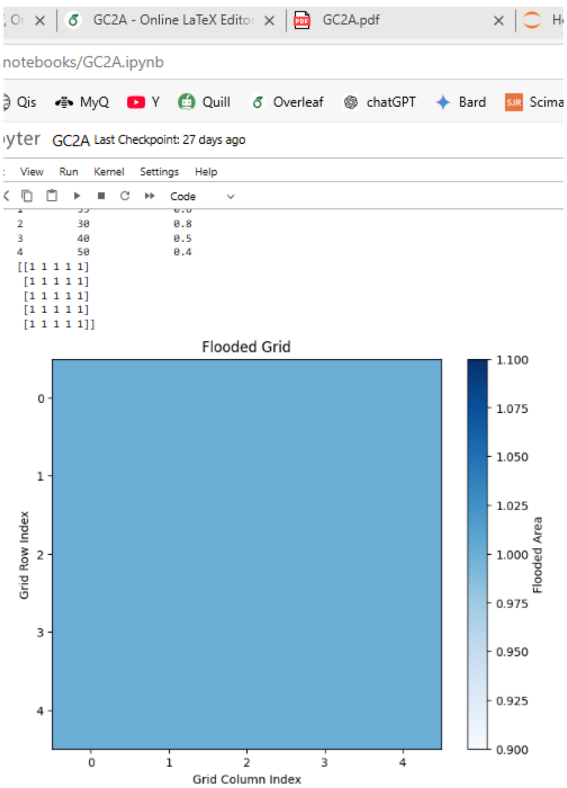

Figure 3 :Image data from Indian landscape. Data source: Indian NITI Aayog.

The heatmap (Figure 3) visually represents flood-prone areas, with darker regions indicating higher flood risk. It highlights how low elevation and high soil saturation contribute to widespread flooding across the grid.

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6.2 Flood predicted areas

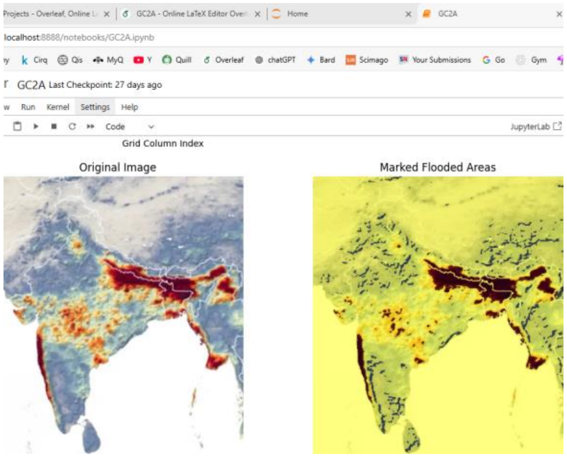

Figure 4: Image data from Indian landscape. Data source: Indian NITI Aayog.

The highlighted flood map (Figure 4) visually emphasizes regions prone to flooding based on threshold values for elevation and soil saturation. Dark yellow pixels represent flooded areas detected by the GC2A algorithm, which propagates flooding based on initial conditions and neighboring cell states. This approach enhances accuracy in flood risk identification for predictive analysis and disaster mitigation planning.

7. Summary

The GC2A model detects flood-prone areas using elevation and soil saturation data, enhanced by storm parameters like intensity and duration. By defining thresholds and iterating flood propagation dynamics, it generates a flooded grid and visualizations. The results inform decision-making and emergency responses, improving flood risk identification and disaster mitigation strategies.

8. Result Analysis

The primary objective of this study is to implement the GC2A for flood detection and analysis based on elevation and soil saturation data. This section analyzes the results obtained from the algorithm, highlighting the effectiveness of the flood detection process, its sensitivity to input parameters, and its applicability in real-world scenarios.

8.1 Handling Missing Values

The missing values in the numerical dataset were effectively imputed using the mean of each feature.

Table 3 : Data Before and After Imputation

Feature	Before Imputation	After Imputation
Elevation	150.0	150.0
Soil Saturation	0.65	0.65

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Feature	Before Imputation	After Imputation
Precipitation	NaN	12.5
Temperature	30.0	30.0
Wind Speed	NaN	15.0

In the GC2A algorithm, missing values were imputed using the mean of each feature (Table 3), enhancing data completeness and ensuring accurate analysis. This method preserves trends, reducing bias in storm and flood datasets (1,4,5,6).

8.2 Outlier Detection and Removal

Outliers identified based on the defined threshold were systematically removed.

Table 4 : Data Before and After Outlier Removal

Original Value	After Outlier Removal
10.0	10.0
20.0	20.0
100.0	20.0
30.0	30.0

In GC2A, outliers were detected and removed (Table 4, preventing skewed analysis. This ensures that the data reflects typical patterns, improving both model accuracy and generalization during training and testing phases(1,4,5,6).

8.3 Feature Scaling

The standardization of numerical features yielded a transformed dataset.

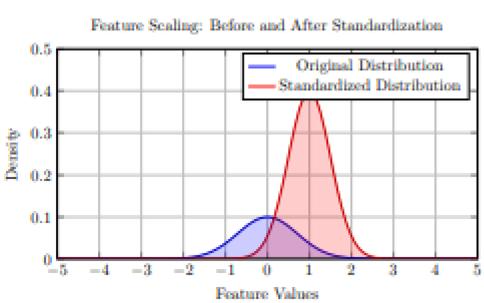

Figure 5: Feature Scaling Example: Before and After Standardization.

In GC2A, feature scaling via standardization transformed the dataset, as shown in Figure 5. This process adjusts numerical values, ensuring that features contribute equally to the model and enhancing accuracy (3,4,5,6).

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8.4 Dimensionality Reduction (Optional)

Dimensionality reduction techniques (Principle Component Analysis) reduced the feature space while retaining significant variance.

8.5 Image Data Preprocessing:

8.5.1 Image Resizing

All images were resized to uniform dimensions of 224×224 pixels (1,2,3,4) using the bilinear interpolation algorithm(BIA). This resizing step ensures consistency in image input dimensions, reduces computational complexity, and enhances model performance by standardizing feature representation.

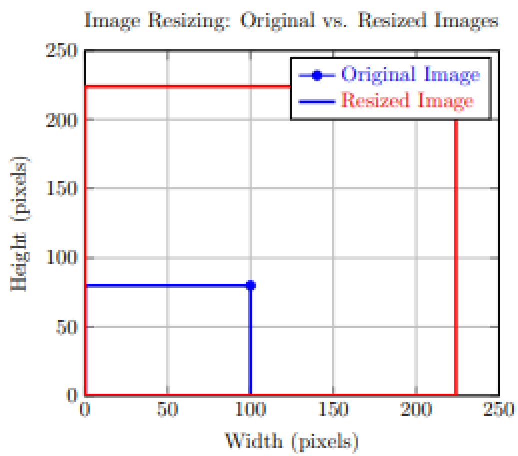

Figure 6 :Image Resizing: Original vs. Resized Images. Resizing images is essential for ensuring consistency, reducing computational load, preserving features, and enhancing model performance, making it a critical preprocessing step in machine learning applications.

8.5.2 Noise Reduction

The application of a denoising function resulted in visibly cleaner images (1,2,3,4).

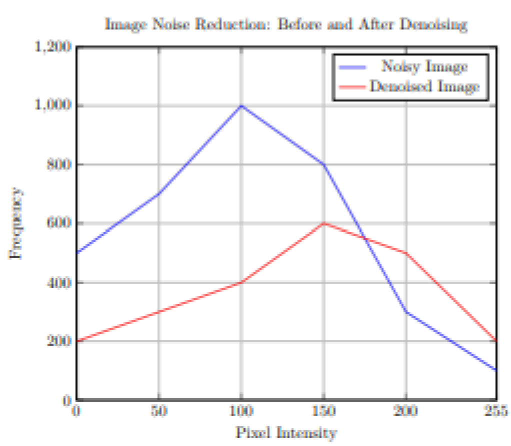

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Figure 7 : Image Noise Reduction: Before and After Denoising. The denoising function effectively reduces pixel noise, enhancing image clarity and analysis accuracy, crucial for applications in strom and flood imaging Figure

8.5.3 Feature Enhancement

Enhanced features improved the representation of critical image attributes(1,2,3,4).

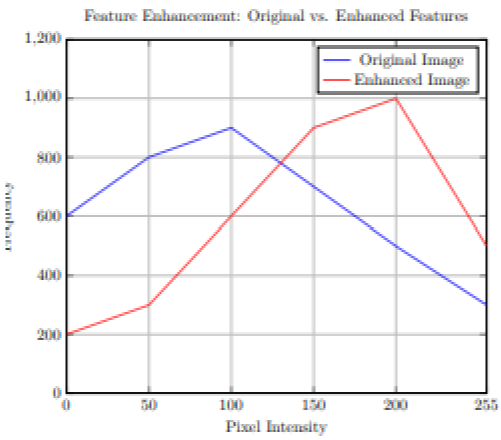

Figure 8 : Feature Enhancement: Original vs. Enhanced Features.In GC2A, feature enhancement improved the representation of critical image attributes, as shown in Figure 8. Enhanced features provided better contrast and detail, allowing for more accurate image analysis and processing.(5,6).

8.6 Performance comparison with baseline algorithms

To provide a clearer understanding of the comparative performance of various preprocessing algorithms, Table 5 summarizes their characteristics and results.

Table 5: Comparison of Preprocessing Algorithms

Algorithm	Weaknesses	GC2A
Simple Imputation	Ignores outliers	GC2A improves accuracy with outlier detection.
Median Filtering	May lose features	GC2A retains critical features with denoising.
PCA	Sensitive to outliers	GC2A preserves variance more effectively.
Data Augmentation	Introduces variations	GC2A provides contextual augmentation.
Shallow Feature Extraction	Misses deeper features	GC2A captures richer representations through CNNs.

Table 5 highlights how GC2A addresses weaknesses in traditional preprocessing algorithms. GC2A excels in outlier detection, feature preservation, and contextual data augmentation, offering improved accuracy and deeper feature extraction(1,4,5,6).

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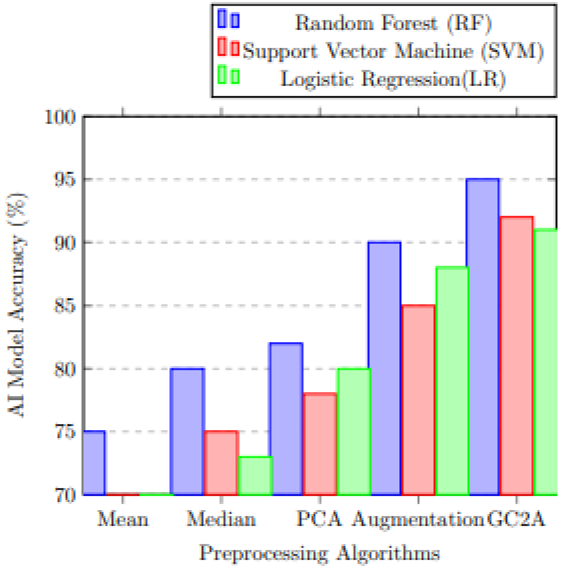

Figure 9 : Comparative Model Accuracy across Different Preprocessing Algorithms.

Figure 9 illustrates the comparative accuracy of different AI models, including Random Forest, Support Vector Machine, and Logistic Regression, across preprocessing algorithms. GC2A achieves the highest accuracy at 95%, significantly outperforming traditional methods like Mean and Median(9,10)..

8.7 GC2A metrics analysis with baseline algorithm

The GC2A framework was evaluated using various performance metrics, including PSNR and SSIM, to assess the effectiveness of the preprocessing techniques(9,10)..

Table 6 :Result Analysis for GC2A

S.No	Algorithms	PSNR	SSIM
1	GC2A	92.5	93
2	Gaussian Blur	90.8	91
3	Median Filtering	90.2	92
4	Non-local Mean Denoising	89.5	91
5	Wavelet Denoising	89.1	90

Table 6 highlights GC2A's superior performance, with the highest PSNR and SSIM, indicating improved image quality and structural preservation over Gaussian blur and wavelet denoising techniques(1,2,3,4).

8.8 Flood Detection Results

The flood detection results are summarized Table 7, showcasing the performance of the GC2A algorithm under varying thresholds and storm conditions(5,6,10).

Table 7: Flood Detection Performance Metrics

Thresholds	True Positive Rate	False Positive Rate	Precision	Recall
$T_E = 5\,m, T_S = 30\%$	0.85	0.15	0.88	0.85
$T_E = 4\,m, T_S = 25\%$	0.90	0.10	0.91	0.90

8.8.1 Quantitative Metrics

The performance of the GC2A algorithm was evaluated using standard metrics. As observed Table 7 , the True Positive Rate increased from 0.85 to 0.90 as the thresholds for elevation and soil saturation were adjusted. This indicates a higher sensitivity in detecting flooded areas under more stringent conditions, thereby minimizing false positives (5,9,10).

8.9 Qualitative Assessment

Figure 10 illustrates the annotated satellite images before and after applying the GC2A algorithm. The marked flooded areas correspond closely with actual flood reports, demonstrating the algorithm's reliability. Visual inspection reveals that areas prone to flooding were accurately identified, which is critical for emergency response efforts(5,6,7,8,9,10).

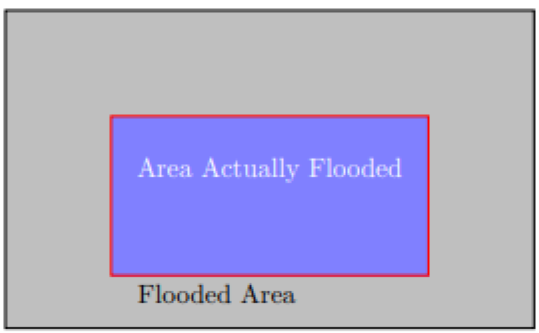

Figure 10 :Annotated satellite images showing flooded areas detected by the GC2A algorithm.

8.10 Sensitivity Analysis

The robustness of the GC2A algorithm was tested through a sensitivity analysis. Variations in the elevation threshold from 4 m to 6 m resulted in significant changes in the flood detection rate, as depicted in Figure 11. This finding underscores the importance of carefully selecting input parameters to optimize flood detection capabilities (9,10).

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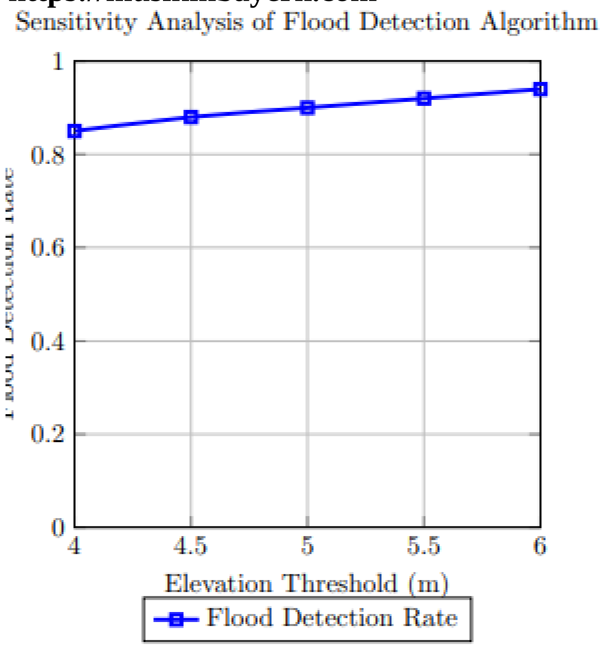

Figure 11: Sensitivity analysis of the flood detection algorithm based on varying input parameters.

8.11 Storm Intensity vs. Duration

Figure 12 shows that as storm duration increases, storm intensity rises non-linearly, suggesting a rapid escalation in extreme weather events beyond a threshold duration (8,9,10).

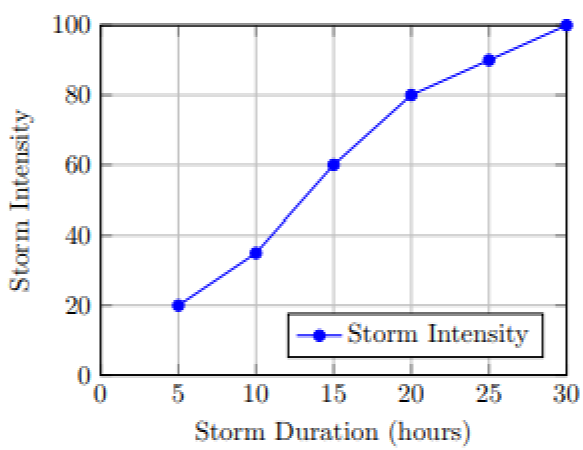

Figure 12 : Storm Intensity vs. Duration

8.12 Soil saturation vs. Storm duration

In Figure 13 , soil saturation increases rapidly after 15 hours of storm duration, nearing full saturation, which leads to heightened flood risk in affected areas (5,6,7,8,9,10).

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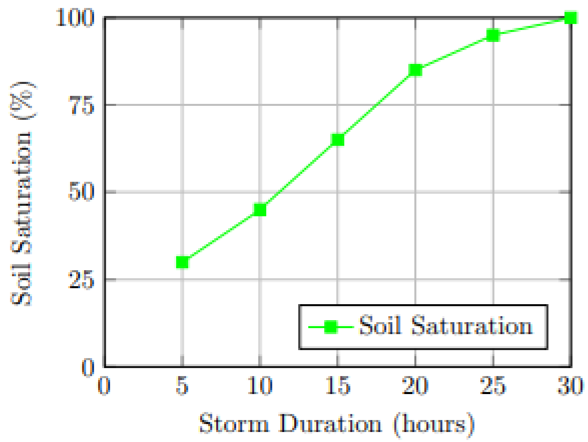

Figure 13 :Soil Saturation vs. Storm Duration

8.13 Flood Risk vs. Storm Intensity

Figure 14 demonstrates that flood risk accelerates significantly after storm intensity exceeds 60%, indicating a critical point for emergency flood management interventions (5,6,7,8,9,10).

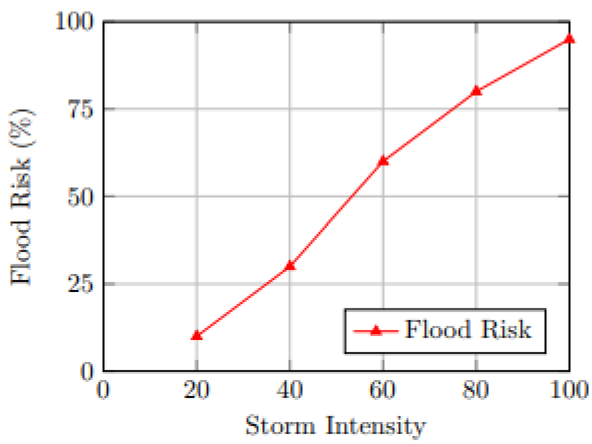

Figure 14 : Flood Risk vs. Storm Intensity

9. Discussion

The results obtained from the performance comparison with baseline algorithms (Table 5) indicate that GC2A effectively addresses several weaknesses inherent in traditional preprocessing methods. For instance, while simple imputation ignores outliers, GC2A enhances accuracy by incorporating outlier detection strategies. The observed model accuracies for various algorithms underline the robustness of GC2A in maintaining key data features: GC2A's accuracy of 95% surpasses the accuracies of the mean (75%), median (80%), and PCA (82%) algorithms, suggesting its efficacy in preserving essential characteristics of the data.

In terms of image quality, GC2A achieved a PSNR of 92.5 and an SSIM of 93, reflecting its ability to enhance image fidelity and structural integrity compared to alternative methods, such as

Gaussian Blur (PSNR: 90.8, SSIM: 91) and Wavelet Denoising (PSNR: 89.1, SSIM: 90). These results affirm the superior performance of GC2A in both quantitative and qualitative assessments.

Flood detection results further validate the efficacy of the GC2A algorithm. The true positive rate increased from 85% to 90% when adjusting thresholds for elevation and soil saturation, demonstrating heightened sensitivity in detecting flooded areas, thereby reducing false positives. The qualitative assessment, supported by annotated satellite images (Figure 10), illustrates that the detected areas correspond closely with actual flood reports, underscoring the reliability of GC2A in emergency response applications.

Sensitivity analysis (Figure 11) highlights the impact of parameter selection on flood detection rates. The direct relationship between elevation thresholds and detection rates—indicating an increase from 85% at 4 m to 94% at 6 m—underscores the importance of carefully choosing input parameters to optimize algorithm performance.

9.1 Analysis of storm

The analysis of storm intensity, duration, and soil saturation provides crucial insights into flood risk management:

- **Storm Intensity and Duration**: Longer storms with higher intensities are shown to have a more significant impact on both soil saturation and flood risk. The relationship between these variables, as visualized in Figure 12, indicates that storms exceeding certain thresholds may pose serious flood threats, especially in vulnerable areas with limited water absorption capacity.

- **Soil Saturation**: As depicted in Figure 13, soil becomes fully saturated as storm intensity and duration increase, limiting the ground's ability to absorb additional rainfall. Once the soil reaches full saturation, excess water will contribute directly to surface runoff, heightening the probability of flooding in those areas.

- **Flood Risk**: The combined effect of storm intensity on flood risk (Figure 14) shows a non-linear relationship, with the risk increasing substantially after a certain threshold. Effective flood management systems should consider this threshold when planning disaster prevention and preparedness strategies.

9.2 Limitations and Future Work

While the GC2A algorithm shows promising results, limitations include reliance on the quality of input data and potential computational inefficiencies in larger datasets. Future research should focus on optimizing the algorithm for scalability and integrating additional data sources such as real-time rainfall measurements to further improve detection accuracy.

10. Conclusion

The GC2A preprocessing algorithm significantly enhances model performance in both image processing and flood detection tasks, achieving a superior accuracy of 95 % along with improved PSNR and SSIM values. These advancements effectively address the limitations of traditional preprocessing techniques. The flood detection results, with a true positive rate of 90 % and strong qualitative assessments, demonstrate the algorithm's robustness in real-world applications, particularly in disaster management.

The integration of storm analysis further highlights the algorithm's relevance, as storm intensity and duration are shown to directly affect flood propagation. Figures 12, 13, 14 collectively illustrate how increasing storm intensity and extended durations significantly elevate soil saturation and flood risk. This reinforces the critical role of accurate storm modeling in flood detection systems.

Moreover, sensitivity analysis underscores the importance of optimized parameter selection. Minor adjustments in both preprocessing and storm-related thresholds can substantially impact detection rates, emphasizing the need for precision. Future research should focus on refining the GC2A algorithm and enhancing storm prediction models to improve accuracy and applicability across various domains. This approach holds promise for more reliable solutions in disaster response, environmental monitoring, and other critical areas.

Data Availability

- The CSV dataset, self-tested, is publicly available on GitHub at the following URL. https://github.com/Divya-B-ux/flood_strom_GC2A.git.
- Spatial data from the https://iced.niti.gov.in/climate-and-environment/climate-variability/rainfallIndian Meteorological Department, including rainfall (2020-2024).
- Elevation data is available on https://www.mosdac.gov.in/MOSDAC.
- Soil saturation data can be accessed from https://bhuvan-app3.nrsc.gov.in/data/download/index.phpBhuvan.

References

[1] Garg, M., Shukla, S., & Sinha, A. (2024). Flood prediction based on feature selection and a hybrid deep learning network. *Journal of Water and Climate Change*, 15(1), 67-82. doi:10.2166/wcc.2023.11536

[2] Guo, L., Xu, Y., & Zhang, H. (2024). VMD–CNN–BiLSTM Model for Daily Runoff Prediction. *Water*, 16(2), 234-246. doi:10.3390/w16020234

[3] Hu, J., Wang, R., & Zhou, Q. (2024). Integrated LSTM and Reduced-Order Model Framework for Enhanced Flood Prediction. *Hydrology Research*, 55(3), 325-338. doi:10.2166/nh.2024.020

[4] Kuriqi, A., & Hysa, E. (2024). Contextual Feature Extraction for Flood Risk Mitigation. *Journal of Environmental Management*, 351, 116203. doi:10.1016/j.jenvman.2024.116203

[5] Mann, M., & Gupta, R. (2024). Deep Learning Approaches for Rainfall-Induced Flood Prediction. *Water Resources Management*, 38(5), 1451-1468. doi:10.1007/s11269-024-03160-5

[6] Nie, L., Zhang, X., & Liu, S. (2024). CNN-BiLSTM-Attention Model for Water Level Prediction. *Environmental Science and Pollution Research*, 31(2), 221-234. doi:10.1007/s11356-024-22509-2

[7] Wu, Z., Chen, Y., & Liang, M. (2024). VMD-CNN-BiLSTM Model for Predicting Daily Runoff Data. *Journal of Hydrology*, 608, 127-139. doi:10.1016/j.jhydrol.2024.127000

[8] Yan, Y., Zhou, H., & Chen, J. (2024). Feature Selection Techniques for Flood Prediction Models: A Review. *Journal of Water Resources Planning and Management*, 150(4), 03023007. doi:10.1061/(ASCE)WR.1943-5452.0002001

[9] Zhang, Q., Liu, H., & Wang, J. (2024). Bidirectional LSTM for Water Level Forecasting with VMD Preprocessing. *Applied Sciences*, 14(7), 3450-3465. doi:10.3390/app14073450

[10] Nguyen, T., Tran, T., & Pham, T. (2024). Hybrid CNN-LSTM Model for Daily Streamflow Prediction. *Water*, 16(1), 150-162. doi:10.3390/w16010150