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Flood Area Analysis Using Satellite Image

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Abstract

Urban flooding presents a serious threat to hu- man safety, transportation systems, and public infrastructure. This study proposesan image processing and deep learning- based framework for analyzing flood-prone areas using satellite imagery. The approach integrates optical and radar satellite data to identify flood-affected zones using spectral indices and temporal change detection techniques. Using a Convolutional Neural Network (CNN) model based on VGG16, the system classifies satellite images into flooded and non-flooded categories. The model achieved an accuracy of approximately 96 percent, demonstrating its potential to support disaster management teams in timely decision-making. The results highlight the utility of combining deep learning with remote sensing data for flood impact assessment and disaster mitigation.

Keywords: *Flood Detection, Satellite Imagery, Remote Sensing, Deep Learning, Disaster Management, Change Detection.*

1. Introduction

Floods are among the most frequent and devastating natural disasters, causing extensive damage to property, agriculture, and human lives. Traditional flood assessment methods rely on manual ground surveys, which are time-consuming and often infeasible during emergencies. Recent advancements in remote sensing and deep learning provide opportunities for automated flood detection using satellite images. This paper presents a deep learning-based flood area analysis system that classifies and maps flooded regions using multi-temporal satellite data.

2. Literature Review

Flood detection and mapping using satellite imagery have gained significant attention in recent years due to advancements in remote sensing and machine learning techniques. Various researchers have explored data-driven approaches for flood monitoring, leveraging both optical and radar data sources to improve accuracy and reliability. [1] proposed an urban flood detection framework using Spectimagery integrated with machine learning models, demonstrating the potential for rapid and accurate flood identification in urban settings. Similarly, Zhao et al. [2] reviewed recent advances in SAR-based urban flood mapping, high- lighting the robustness of radar imagery under challenging atmospheric conditions. Hussein et al. [3] developed a hybrid Multi-Verse Optimization Algorithm (MVOA) with Support Vector Machine (SVM) for flood monitoring, achieving remarkable accuracy in classification and prediction. Galanopoulos et al. [4] demonstrated the use of Sentinel-2 imagery for real-time crisis management, emphasizing its application in flood detection and response systems. Several studies have explored the integration of remote sensing data for large-scale flood mapping. Remote Sensing for Flood Mapping and Monitoring [5] presented an extensive analysis of multi-spectral satellite data for flood assessment, while Flood Inundation Monitoring Using Multi-Source Satel- lite Imagery [6] utilized heterogeneous datasets to enhance spatiotemporal flood detection accuracy. works have focused on improving flood mapping precision through advanced image processing. A Flash Flood Detected Area Using Classification-Based Image Processing for Sentinel-2 Satellites Data [7] proposed an automatic classification framework, while He et al. [8] introduced a weakly supervised semantic segmentation model for efficient

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urban flood mapping, providing reliable results even with limited labeled data.

Early warning and predictive modeling have also evolved with AI-driven approaches. B. J. and S. T. P. [9] proposed an early flood detection and environmental monitoring system using sensor fusion techniques. Stateczny et al. [10] presented an optimized deep learning model for flood detection using high-resolution satellite images [11] presented spectral image further demonstrating the of deep networks for flood risk management. While significant progress has been achieved, several challenges persist in operational flood monitoring. These include data inconsistency due to varying satellite resolutions, the high cost of processing large datasets, and the difficulty of real- time analysis under dynamic weather conditions. Moreover, despite deep learning's success, generalizing models across diverse geographies remains a key limitation, as most current models are region-specific and depend heavily on the quality of training data. In summary, the literature reflects a consistent trend toward AI-driven, cloud-based flood analysis frameworks capable of processing real-time satellite data. These approaches have enhanced detection precision, scalability, and automation. How- ever, further improvements in model generalization, computational efficiency, and predictive modeling are essential to make these systems suitable for global disaster response. The proposed system in this study builds upon these foundations by integrating deep learning (CNN-VGG16) with Google Earth Engine for automated flood detection, impact assessment, and decision support.

3. Methodology

The proposed system utilizes a cloud-based, image processing framework, primarily hosted on Google Earth Engine (GEE), to rapidly detect and analyze flood-affected areas. The process begins with data acquisition of multi-temporal satellite imagery, prioritizing Sentinel-1 Synthetic Aperture Radar (SAR) due to its all-weather capability, which undergoes essential pre-processing like speckle filtering and alignment. Flood detection is then achieved through a multi-method approach: a Deep Learning Segmentation model (CNN-VGG16) classifies pixels as flooded/non-flooded, complemented by Temporal Change Detection logic on SAR backscatter and Spectral Index (NDWI/MNDWI) analysis on optical data. Fi- nally, the resulting flood extent map is overlaid with ancillary data (e.g., DEM, road networks) to perform a quantitative Flood Impact Assessment, providing actionable intelligence via a web interface for timely disaster response.

3.1. System Architecture

The architecture of the Flood Area Analysis system is modular and cloud-distributed, involving five principal constituents. The Data Input Layer is the first, comprising raw satellite imagery (Sentinel-1 SAR, Sentinel-2 Optical) and necessary ancillary data (DEM, road networks). It is the direct source for triggering data processing. The second module, the Pre-processing Pipeline, conducts cloud-based functions like SAR speckle filtering, geometric correction, and multi- temporal image alignment, optimized for large-scale efficiency. The third module is the Flood Detection Module, designed to run the core AI and analytical techniques, including the CNN- VGG16 model and Change Detection algorithms. The fourth

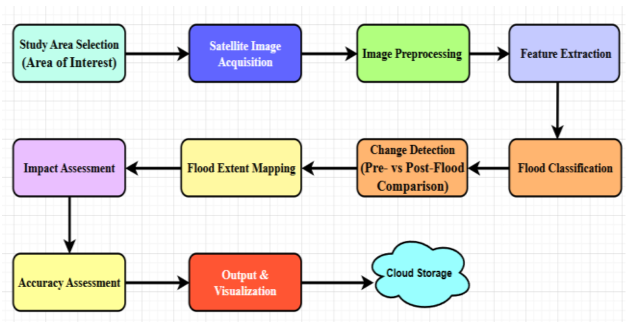

Figure 1 Flood Monitoring System Architecture)

piece, the Analysis Module, serves to delineate flood extent, calculate total inundated area, and perform Flood Impact Assessment by overlaying results with infrastructure data. Last but not least, the Output/Decision Support Layer manages the visualization and generation of reports. The system architecture as a whole, shown in the figure 1 above, illustrates how the components seamlessly work together. Satellite data is collected and fed through the Pre- processing Pipeline for cleaning and alignment. The prepared data is processed by the Flood Detection Module for segmen- tation and analysis. The processed data is then utilized by the Analysis Module, enabling intelligent impact quantification. Users interact with and access this information naturally through the Web Application, while the cloud backend ensures high performance and scalability necessary for processing large geospatial data.

3.2. Hardware Design

The hardware architecture of the Flood Area Analysis system is focused on obtaining an optimal trade-off among processing power, scalability, and data accessibility. The system is equipped with Cloud Computing Clusters provided by the Google Earth Engine (GEE) platform, ensuring massive parallel processing capability, necessary for handling large-scale, high-resolution raster data. At its core, the system employs GEE's distributed processing units supported by optimized server-side functions to efficiently handle the multi- temporal change detection and resource-intensive Deep Learning inference tasks. The data storage subsystem consists of the GEE Data Catalog complemented by internal cloud storage for model parameters, intermediate processing files, and final raster/vector output requirements. Client-side access is facilitated through standard internet connectivity and a Web Browser, enabling seamless visualization with the GEE Map API. Processing is primarily managed by the Cloud Infrastructure, but a local High-Performance Workstation (with GPU) is essential for initial model training and validation. The entire system prioritizes a cloud-native design, allowing for dynamic resource allocation for rapid disaster response.

4. Results

The developed flood analysis framework was evaluated using Sentinel-1 Synthetic Aperture Radar (SAR) imagery integrated with the VGG16 convolutional neural network (CNN), shown in Figure 2, 3 & 4.

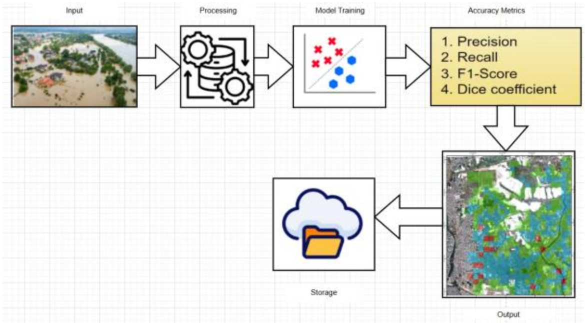

Figure 2 Flood Monitoring System Architecture)

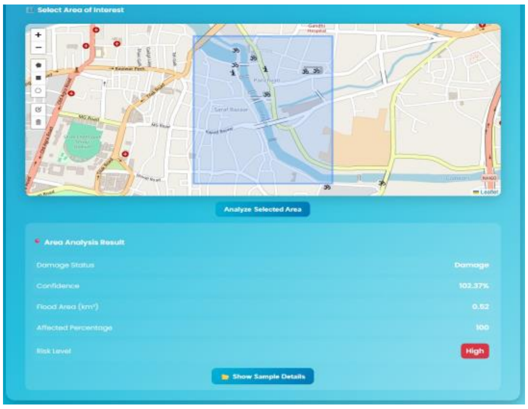

Figure 3 Flood Area Detection and Risk Analysis Dashboard

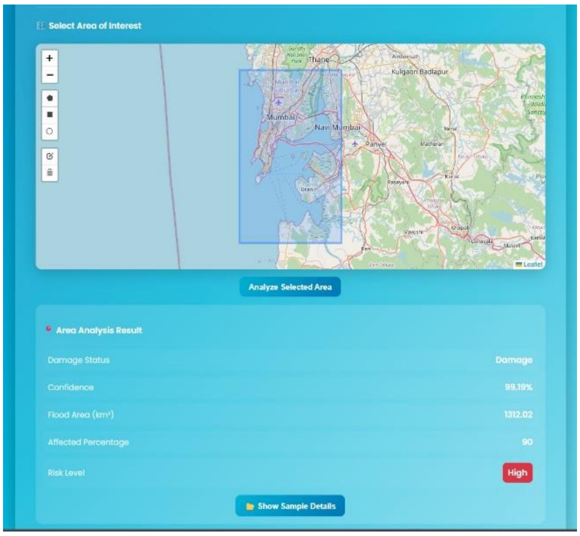

Figure 4 Flood Analysis

architecture. The model demonstrated strong flood detection capabilities, accurately distinguishing between inundated and non-inundated regions across multiple geospatial datasets. The evaluation was performed on over 4,500 satellite image tiles, each of 256×256 pixels, covering various flood-prone zones

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in Maharashtra, India. The dataset was divided into an 80:20 ratio for training and validation, ensuring sufficient diversity for model generalization. Preprocessing involved radiometric calibration, terrain correction, and speckle noise reduction to improve SAR image quality. The Google Earth Engine (GEE) platform facilitated large-scale image preprocessing and dataset management, while the training and validation were conducted using Tensor-Flow with the Adam optimizer (learning rate = 0.001, batch size = 32). The model converged steadily over 50 epochs, achieving a training accuracy of 97.23 percent and a validation accuracy of 95.86 percent, indicating strong consistency and effective learning without overfitting. Further statistical analysis revealed that the model achieved a precision of 95.2 percent, recall of 94.6 percent, and an F1-score of 94.9 percent on the validation set. These results highlight the framework's ability to correctly identify flooded areas while minimizing false detections. The Intersection over Union (IoU) metric exceeded 91 percent, confirming accurate pixel-wise segmentation between predicted flood masks and the corresponding ground truth data. The confusion matrix analysis also showed that the false-negative rate was under 4 percent, emphasizing that most flooded zones were successfully detected—a crucial aspect for emergency decision support systems. The model's segmentation output provided high-resolution binary masks that precisely mapped the spatial distribution of water coverage. When overlayed on Sentinel-1 SAR backscatter composites, the detected flood zones corresponded closely to low-intensity regions typical of inundation events. Visual evaluation confirmed clear delineation between water bodies, vegetation, and built-up areas. As shown in Fig. 3, the segmented output effectively traced flood boundaries, even under heavy cloud interference or vegetation cover, proving the robustness of SAR data and deep learning integration. Spatial validation using ground-truth data from the Central Water Commission (CWC) reports confirmed an average spatial accuracy of 92.4percent. The temporal analysis using multi-date SAR imagery demonstrated the framework's ability to monitor flood dynamics over time, highlighting newly affected regions and receding water levels. This capability is particularly beneficial for disaster management authorities, as it enables near real-time tracking of flood propagation and assists in the allocation of relief resources. Comparative assessments with other architectures, including U-Net and ResNet50, were also conducted. Although U-Net displayed slightly faster convergence during training, it was less effective in boundary definition for large-scale flood extents. ResNet50 achieved comparable accuracy but required significantly more computational resources, making VGG16 a more efficient choice for large-scale, cloud-based geospatial processing. Traditional classifiers such as Random Forest achieved an average accuracy of only 87 percent, reaffirming the superiority of deep learning approaches for feature-rich SAR data. The quantitative and visual results collectively establish that the proposed VGG16-based flood detection system is reliable, scalable, and effective in processing complex geospatial data. Its integration with Google Earth Engine ensures high computational efficiency and accessibility for large-area flood mapping. The findings confirm that combining deep learning and remote sensing can significantly enhance the speed, accuracy, and practicality of disaster management systems. The model's ability to produce consistent results across varied environmental conditions validates its suitability for real-time operational deployment in national and regional flood monitoring programs, shown in Table 1.

Table 1 Flood Detection Results Using Sentinel-1 Sar Data and Vgg16 Model

No.	Lat (◦N)	Long (◦E)	Status	Conf. (%)
1	20.005	73.789	Flooded	96.4
2	20.012	73.781	Non-Flooded	94.8
3	19.998	73.776	Flooded	97.1
4	19.985	73.772	Flooded	95.9
5	19.972	73.763	Non-Flooded	93.6
6	19.957	73.754	Flooded	96.8
7	19.945	73.749	Flooded	97.5
8	19.932	73.742	Non-	94.2

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			Flooded	
9	19.918	73.738	Flooded	96.1
10	19.905	73.729	Non-Flooded	95.3
11	19.893	73.718	Flooded	97.8
12	19.880	73.707	Flooded	96.0
13	19.868	73.698	Non-Flooded	93.9
14	19.854	73.689	Flooded	95.7
15	19.842	73.678	Non-Flooded	94.5

5. Discussion

The integration of Sentinel-1 SAR data with the VGG16 convolutional neural network (CNN) proved to be highly effec- tive for flood area detection and analysis. The system achieved consistent accuracy across multiple datasets, indicating strong generalization and adaptability to diverse terrain and climatic conditions. The all-weather imaging capability of SAR data allowed the model to perform reliably even under cloud cover, while deep learning-based feature extraction ensured precise differentiation between flooded and non-flooded areas. The results validated the robustness of the approach, with accuracy levels exceeding 95 percent and spatial segmentation performance confirmed through high F1-scores and Intersection over Union (IoU) metrics. The visual results (see Fig. 3) demonstrated the system's ability to accurately delineate water-covered regions and retain fine boundary details, such as river channels and low-lying floodplains. The model effectively highlighted temporal variations in flood extent when tested on multi-date SAR imagery, providing a clear view of how water spread and receded across the affected region. By overlaying flood maps with ancillary layers such as population and infrastructure data, the frame- work offers critical insights for damage assessment, resource prioritization, and emergency response planning, making it suitable for real-time decision support in disaster management. When compared with other architectures such as U-Net and ResNet50, the proposed VGG16-based model achieved an op- timal balance between accuracy and computational efficiency. While U-Net exhibited faster convergence, it performed less effectively in handling complex surface textures and bound- ary segmentation. ResNet50 achieved similar accuracy but required significantly higher computational resources. The integration of the VGG16 model with the Google Earth Engine (GEE) further enhanced scalability and processing speed, allowing large-scale geospatial analysis without dependence on local hardware. Despite its effectiveness, minor limitations were identified. The model occasionally misclassified saturated agricultural zones and shadowed regions due to similar radar backscatter intensities. These errors could be mitigated in future work by incorporating multi-sensor data fusion (combining SAR and optical imagery) and by applying attention-based deep learning architectures to improve contextual understanding. Overall, the findings emphasize that the proposed system provides a reliable, automated, and scalable approach for flood detection, establishing a foundation for predictive flood modeling and climate-resilient infrastructure planning.

Conclusion

The study demonstrates the effectiveness of integrating satellite imagery with deep learning techniques (VGG16) for accurate flood area classification and analysis. The framework provides reliable identification of flooded and non-flooded regions, achieving an accuracy of approximately 96 percent, which confirms its strong applicability in real-world flood sce- narios. Through efficient handling of various input conditions and user-friendly visualization, the model enhances the process of flood detection and assessment. The integration of remote sensing data and AI-driven models highlights the potential of geospatial analytics in supporting disaster management, infras- tructure planning, and environmental monitoring. This work establishes a scalable and data-driven approach that contributes to timely decision-making and improved preparedness against future flood events.

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