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Satellite-based Flood Detection

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Abstract: *Flooding poses a significant threat globally, leading to immense economic losses and human displacement. Accurate and timely detection of flood-affected areas is critical for disaster management and response planning. This paper introduces FloodSee, an automated system for flood detection using satellite imagery. The system leverages data from the Sentinel-1 and Sentinel-2 satellites and employs a fine-tuned ResNet-50 deep learning architecture for classification. By combining radar and optical imagery, FloodSee overcomes challenges such as cloud cover and provides robust detection capabilities. Experimental results demonstrate the model's high accuracy, highlighting its potential for operational deployment in flood monitoring and mitigation systems.*

Keywords: Flood detection, ResNet-50, Sentinel-1, Sentinel-2, disaster management, satellite imagery, remote sensing

I. INTRODUCTION

Floods are among the most frequent and devastating natural disasters, disrupting millions of lives and causing widespread damage to infrastructure and agriculture. With climate change increasing the frequency and intensity of extreme weather events, the need for effective flood monitoring systems has become more urgent. Remote sensing, enabled by satellite imagery, offers a scalable and efficient approach to monitoring floods across large areas.Manual interpretation of satellite data is labor- intensive and often impractical during emergencies.Traditional rule-based algorithms, while faster, fail to handle the variability in flood scenarios, such as cloud-covered regions or diverse terrains. This research introduces *FloodSee*, an automated flood detection system that employs Sentinel-1 and Sentinel-2 data in conjunction with ResNet-50, a deep learning model fine-tuned for flood classification. FloodSee provides a high-accuracy, scalable solution capable of rapid response in flood-prone areas.

Satellite-based remote sensing has emerged as a vital tool for monitoring floods, offering the capability to cover large geographic areas with high temporal and spatial resolution. Among the available platforms, Sentinel-1 provides radar-based Synthetic Aperture Radar (SAR) imagery, enabling flood detection under challenging conditions such as cloud cover or nighttime. Sentinel-2 complements this with high- resolution multispectral optical imagery, which is valuable for detailed analysis of flood-affected areas Satellite remote sensing has emerged as a cornerstone technology for flood detection and management due to its ability to cover vast geographic areas with high temporal and spatial resolution. Sentinel-1, with its radar-based Synthetic Aperture Radar (SAR) capabilities, is particularly advantageous for all-weather and day-night monitoring, making it ideal for flood detection under cloudy conditions. Meanwhile, Sentinel-2, equipped with high-resolution multispectral optical sensors, offers detailed imagery that can complement SAR data by providing additional spectral information.

II. LITERATURE REVIEW

1. Project Title: Flood Risk Mapping and Prediction Using AI. : Flood risk mapping has emerged as a critical component of disaster management. Studies have explored the integration of geospatial data and machine learning algorithms to predict flood-prone areas. Techniques such as Random Forest and Gradient Boosting have been employed to analyze topography, rainfall patterns, and historical flood data. Recent advancements in AI highlight the use of convolutional neural networks (CNNs) to extract features from satellite images for accurate flood mapping. However, challenges remain in model scalability, data quality, and real-time prediction accuracy. This research aims to refine risk prediction frameworks and enhance decision-making in flood-prone regions.

Project Title:Post-Disaster Infrastructure Damage Detection Using Drone Imagery

Infrastructure damage detection post-disaster has been a focus of various studies, leveraging aerial imagery and computer vision techniques. Research has demonstrated the potential of AI models such as ResNet and U-Net for damage classification and segmentation. The application of semantic segmentation enables precise damage localization in buildings, roads, and bridges. However, limitations like occlusions in images, lack of annotated datasets, and computational costs hinder the practical implementation. This project aims to bridge these gaps by developing a robust framework for infrastructure assessment, providing essential data for recovery planning.

Project title: Automated Flood Relief Resource Allocation Using AI

The efficient distribution of relief resources during floods is a critical yet complex logistical task. Traditional methods rely on static allocation plans, which are often ineffective in dynamic disaster situations. AI-based solutions have been explored to address this, combining optimization techniques and real-time data for adaptive resource allocation.

Research demonstrates the use of optimization algorithms, such as genetic algorithms, to solve resource allocation problems by simulating multiple scenarios. More recently, Reinforcement Learning (RL) models have been applied, allowing systems to "learn" optimal strategies based on past disasters.

Key limitations include the lack of real-time integration of flood data, as well as difficulties in accounting for unpredictable variables like changing weather conditions or sudden population movements. This project proposes a hybrid approach that combines RL with IoT data from flood sensors, drones, and community feedback. The system will provide dynamic and efficient resource allocation to minimize response times and maximize aid effectiveness.

Project title: Predictive Flood Insurance Model Using AI

Project title: Early Flood Detection Using IoT Sensors and Deep Learning. *Early flood detection systems have traditionally relied on threshold-based models that monitor water levels and weather conditions. While effective in some scenarios, these methods are prone to false alarms and often lack predictive capabilities. IoT (Internet of Things) networks are now being used to gather real-time data from sensors placed in flood-prone areas, such as rivers, dams, and urban drainage systems.Studies explore the use of time-series analysis models, including Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), to predict floods based on sensor data. These models are well-suited for capturing temporal dependencies in data, such as rising water levels or continuous rainfall. Additionally, hybrid models combining LSTM with Convolutional Neural Networks (CNNs) have shown promise in improving prediction accuracy.*

Challenges include sensor malfunctions, data
transmission issues, and overfitting in deep learning models due to small datasets. This project will integrate IoT networks with robust AI models to develop a reliable early warning system, ensuring timely alerts and minimizing flood-related damages.

Project title: Flood Impact Analysis and Recovery Monitoring Using Sentinel Data.

Analyzing the impact of floods and monitoring recovery efforts are essential for effective disaster management. Sentinel-1 and Sentinel-2 satellites, with their high- resolution radar and optical imaging capabilities, have been widely used for flood impact assessment. Research in this area focuses on change detection algorithms that compare pre- and post-disaster imagery to identify flooded areas and assess damage. Object detection frameworks such as Mask R-CNN and transfer learning methods have been utilized to analyze Sentinel data, enabling accurate classification of affected infrastructure and vegetation. However, issues like low- resolution imagery, high computational demands, and the need for domain-specific training data limit the effectiveness of these methods. This project will address these limitations by implementing advanced ResNet-based architectures optimized for Sentinel data. The focus will be on improving the accuracy of flood extent mapping and supporting recovery monitoring by providing insights into vegetation regrowth, infrastructure repair, and population resettlement efforts..

Project title: Real-Time Flood Evacuation Route Planning Using AI.

Flood insurance systems are often reactive, with premiums based on historical data and outdated risk assessments. Predictive modeling can revolutionize flood insurance by providing accurate, data-driven risk estimates. Recent studies have used regression models and Bayesian networks to predict the likelihood and severity of flooding in specific regions.Deep learning models, such as Gradient Boosting Machines (GBM) and XGBoost, have been employed to analyze diverse datasets, including rainfall patterns, topography, and historical flood records. While these models improve prediction accuracy, they often lack transparency, leading to difficulties in policyholder trust.

This project aims to develop a predictive flood insurance model using Explainable AI (XAI) techniques. The model will analyze environmental and socioeconomic factors to provide personalized insurance plans, ensuring affordability and fairness while improving insurers' risk management strategies.

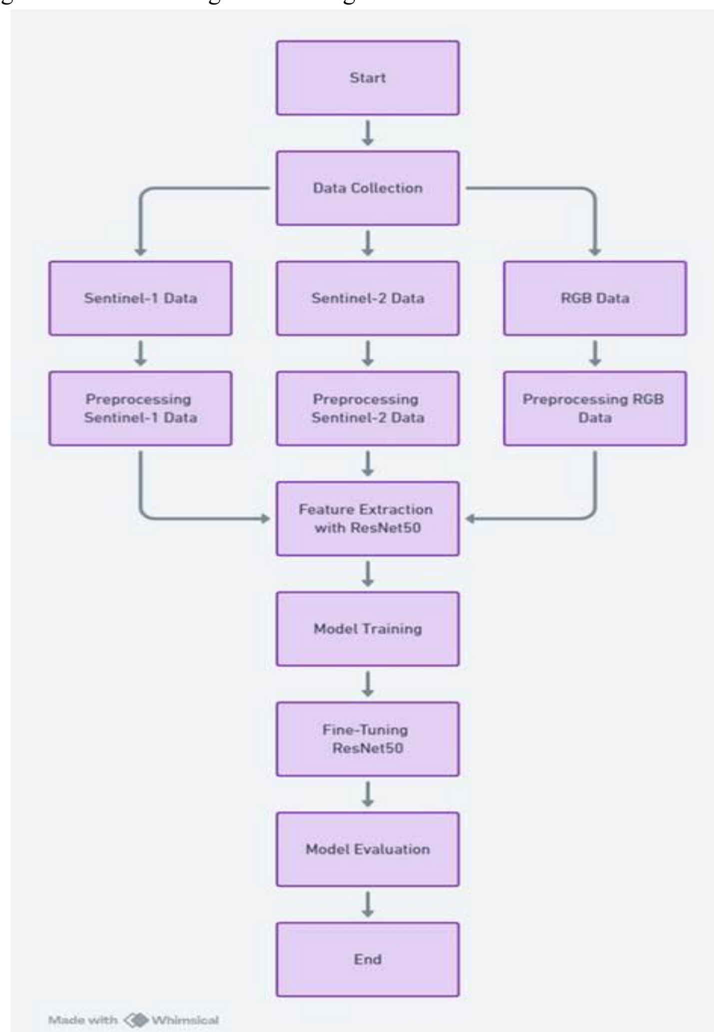

Fig 1.1 System Architecture.

Floods often lead to disrupted transportation networks, making evacuation route planning a critical challenge. Traditional methods use static maps and fixed plans, which fail to adapt to rapidly changing flood scenarios. AI- based solutions can dynamically generate and update evacuation routes using real-time data from IoT sensors, weather reports, and satellite imagery.Recent research highlights the application of graph-based algorithms like Dijkstra's and A* for shortest path calculations. However, these approaches often fail to account for dynamic variables like rising

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floodwaters or blocked roads. Reinforcement Learning (RL) models, trained on simulated flood scenarios, have been proposed for adaptive route planning, but they require extensive computational resources.This project focuses on developing a hybrid model combining graph-based algorithms and machine learning for real-time evacuation routing. The integration of drone imagery and flood sensor data will ensure that routes are continuously updated, providing safe and efficient evacuation paths for affected communities

III. SYSTEM ANALSIS

Objective

The primary objective of this research is to develop an automated flood detection system, *FloodSee*, that leverages satellite imagery from Sentinel-1 and Sentinel-2. By fine-tuning the ResNet-50 deep learning architecture, the system aims to accurately classify flooded and non- flooded regions under diverse environmental conditions. The integration of radar and optical data ensures robustness against challenges such as cloud cover and varying terrain, enabling timely and reliable flood monitoring for disaster response and management.

RESNET 50

short for Residual Neural Network with 50 layers, is a deep learning model widely used for tasks like image classification, object detection, and feature extraction. It excels due to its residual learning approach, which addresses the vanishing gradient problem by introducing skip connections that bypass certain layers, allowing the network to learn effectively even with increased depth. RESNET 50 processes input images, such as orthophotos, by extracting features at multiple levels—starting with basic edges and textures in the initial layers and advancing to complex patterns in the deeper layers. This model is highly relevant for flood detection projects, as it can analyze satellite imagery, such as Sentinel-1 and Sentinel-
2 data, to accurately identify flood-affected regions, distinguish water bodies, and provide detailed insights for disaster response and management. Its robust architecture makes it well-suited for handling the complexity of real-world scenarios, offering high accuracy and efficiency in extracting meaningful patterns from large datasets.

TensorFlow/Keras

TensorFlow, along with its high-level API Keras, is a powerful open-source library for building and deploying machine learning and deep learning models. It offers a versatile framework for designing neural networks, from simple sequential architectures to complex multi-branch networks. Keras simplifies the model-building process by providing an intuitive interface with prebuilt layers, loss functions, optimizers, and metrics. TensorFlow is particularly effective for large-scale computations, leveraging GPU acceleration for faster training and deployment of deep learning models. Its support for production-level tools, such as TensorFlow Lite and TensorFlow Serving, makes it a go-to library for both research and real-world applications like flood detection and satellite image analysis.

Matplotlib

Matplotlib is a robust library for creating static, interactive, and animated visualizations in Python. It provides tools for plotting data in various formats, including line graphs, scatter plots, heatmaps, and histograms. In the context of flood detection, Matplotlib is invaluable for visualizing trends, such as water level changes, flood extent, and prediction outputs from models. It enables clear representation of geospatial data and model performance metrics, making it easier to communicate results to stakeholders and refine analytical methods.

PyTorch

PyTorch is an open-source deep learning framework known for its flexibility, ease of use, and dynamic computational graph, making it a favorite among researchers and developers. It allows for the seamless development of neural networks with its intuitive tensor operations and a rich library of prebuilt layers, loss functions, and optimization algorithms. PyTorch supports both CPU and GPU acceleration, enabling efficient training of models on large datasets. Its dynamic computation graph allows developers to modify and debug models in real-time, offering unmatched versatility during experimentation. In flood detection projects, PyTorch can be used to build and train custom models, such as RESNET-50, to process satellite imagery and identify flood-affected areas. The framework also integrates well with data handling libraries like Pandas and visualization tools like Matplotlib, streamlining the end- to-end development pipeline.

Sentinel-1 and Sentinel-2 Datasets

Sentinel-1 and Sentinel-2, part of the European Space Agency's Copernicus program, provide complementary datasets for Earth observation. Sentinel-1 uses radar imaging to capture all-weather, day-and-night data, making it ideal for flood detection during adverse conditions by accurately identifying water bodies. Sentinel-2 complements this with multispectral optical imagery across

13 bands, offering detailed insights into water spread, sedimentation, and vegetation damage. Together, these datasets provide a comprehensive view of flood events, combining radar's surface analysis with optical spectral insights, ensuring accurate and timely disaster management solutions

Proposed Method

For the proposed flood detection method, the process begins with the collection and preprocessing of Sentinel-1 and Sentinel-2 datasets. The Sentinel-1 data, which uses Synthetic Aperture Radar (SAR), is utilized to capture radar-based imagery that can penetrate clouds and darkness, making it effective for detecting water bodies under any weather condition. The Sentinel-2 data, which provides multispectral optical imagery, is used to analyze vegetation, water bodies, and soil, offering valuable insights into flood extent and damage. The preprocessing stage involves extracting key features from both datasets: Sentinel-1’s dual-polarization backscatter coefficients (VV and VH) are used to identify water, while Sentinel-2's spectral indices like NDVI and NDWI help distinguish between water, vegetation, and soil.After preprocessing, the next step is to align both Sentinel-1 and Sentinel-2 images spatially and temporally to ensure that the data from both sources match accurately. Once aligned, the datasets are combined to leverage both radar and optical insights for a more comprehensive understanding of the flood-affected areas. Following this, a deep learning model based on RESNET-50 is employed for feature extraction and classification. RESNET-50 is trained on the combined dataset to identify flood zones, leveraging its ability to extract hierarchical features from the images. The model is fine-tuned to distinguish between flooded and non-flooded areas based on the combined radar and optical data inputs.Finally, the output of the RESNET-50 model is analyzed and visualized using tools like Matplotlib, providing graphical representations of flood-affected regions. This visualization helps in disaster response by identifying critical areas that require immediate attention. The proposed method combines the strengths of both Sentinel datasets with deep learning to enable efficient, accurate, and timely flood detection.

Sentinal 1 - 2 Dataset

In your flood detection project, Sentinel-1 and Sentinel-2 datasets are essential for accurately identifying flood-affected areas. Sentinel-1, with its Synthetic Aperture Radar (SAR) capabilities, is particularly valuable as it captures radar-based images that can penetrate cloud cover and work in any weather condition, allowing continuous monitoring even during heavy rainfall or storms. This makes Sentinel-1 ideal for detecting water bodies in flood-prone regions, especially in situations where optical data may be obscured by clouds. By analyzing the backscatter coefficients from Sentinel-1’s radar data, your project can identify water surfaces and flood zones accurately, even in challenging conditions.On the other hand,

Sentinel-2 provides multispectral optical imagery, which adds another layer of insight. Its 13 spectral bands, including visible and infrared, allow you to detect changes in vegetation and water bodies more precisely. By calculating indices like NDVI (Normalized Difference Vegetation Index) and NDWI (Normalized Difference Water Index), you can distinguish between flooded areas, vegetation, and other land surfaces. This helps to validate the flood extent detected by Sentinel-1 and adds more detail to the analysis.

Together, the combination of Sentinel-1's radar-based imaging and Sentinel-2's multispectral optical data enhances your project's ability to detect floods with high accuracy, even under varying environmental conditions. The datasets work together to provide both temporal and spatial insights, ensuring that flood-affected regions are detected and mapped comprehensively, aiding in real-time disaster response and management.

Preprocessing Steps for Flood Detection Using Sentinel-1 and Sentinel-2 Data

Preprocessing is a crucial step in ensuring that the raw Sentinel-1 and Sentinel-2 data is clean, aligned, and ready for analysis. For flood detection, it is essential to extract relevant features and align both datasets so they can be used in combination to improve model accuracy. Below are the key preprocessing steps used in this project:

Data Acquisition:

The first step involves acquiring the Sentinel-1 and Sentinel-2 data from the Copernicus Open Access Hub. The data typically comes in the form of GeoTIFF files, with different resolutions and spatial coverage. Both Sentinel-1 and Sentinel-2 images must be selected based on the geographical area of interest and the time period of the flood event being analyzed.

Radiometric Correction:

Raw satellite images often contain noise and discrepancies due to atmospheric conditions, sensor inconsistencies, and other factors. Radiometric correction is applied to adjust the image data, ensuring that the pixel values reflect the true reflectance of the Earth's surface. This correction helps minimize any errors caused by atmospheric scattering, ensuring that the data accurately represents the observed features, particularly in the context of water bodies and flood zones.

Geometric Correction and Co-Registration:

Sentinel-1 and Sentinel-2 datasets are captured using different sensors and platforms, meaning that the images may not be perfectly aligned. Geometric correction and co- registration are necessary to align the two datasets spatially. This step ensures that the pixel coordinates in both images correspond to the same locations on the Earth's surface. Co-registration is especially important when combining Sentinel-1's radar-based data with Sentinel-2's optical data to analyze flood events across the same geographic region.

Temporal Alignment:

Since Sentinel-1 and Sentinel-2 provide data at different times, it is important to align the data temporally. This involves selecting images from both satellites that correspond to the same time period to ensure that the flood event is captured consistently across both datasets. Temporal alignment is particularly important for detecting flood changes over time and comparing pre- and post- flood conditions.

Cloud Masking and Cloud Shadow Removal:

Sentinel-2 images, being optical, are often affected by cloud cover, especially during flood events. Cloud masking is applied to remove the influence of clouds and cloud shadows in the imagery. This is done using automatic cloud detection algorithms based on the spectral characteristics of clouds. For instance, Sentinel-2's shortwave infrared bands (SWIR) can be used to identify and mask out cloud and cloud shadow pixels, ensuring that only the relevant surface data remains for flood detection.

Feature Extraction:

After the geometric and radiometric corrections, relevant features are extracted from both datasets. For Sentinel-1, the key features involve backscatter values from radar data, which are used to distinguish between water and non-water surfaces. The dual-polarization bands (VV and
VH) are particularly important, as they provide insights into surface roughness and water presence. In Sentinel-2, spectral indices such as the Normalized Difference Water Index (NDWI) and Normalized Difference Vegetation Index (NDVI) are computed. NDWI is particularly useful for identifying water bodies, as it emphasizes the difference

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between water and land surfaces, while NDVI helps detect vegetation, which can be useful in differentiating between flooded vegetation and non-flooded areas.

Data Normalization and Resampling:

To ensure that both Sentinel-1 and Sentinel-2 data can be input into the deep learning model effectively, the data is normalized. This step involves scaling pixel values so that they fall within a consistent range, typically between 0 and 1. Additionally, if the spatial resolution of the Sentinel-1 and Sentinel-2 datasets differs, resampling is applied to bring both datasets to the same resolution. This is important because inconsistent resolutions could lead to inaccurate feature extraction and model performance. The resampled datasets are then aligned to the same grid to ensure accurate spatial analysis.

Integration of Sentinel-1 and Sentinel-2 Data for Flood Detection

Integrating Sentinel-1 and Sentinel-2 data combines the strengths of radar and optical imagery, providing a more comprehensive solution for flood detection. Sentinel-1's radar data is unaffected by weather conditions like cloud cover, making it ideal for detecting water bodies in all conditions, while Sentinel-2's optical imagery offers detailed spectral information, especially for identifying changes in vegetation and water bodies.To integrate the data, the first step is to ensure both datasets are spatially and temporally aligned. This involves resampling the data to the same resolution and matching the time periods of the images. Next, relevant features are extracted from both datasets: Sentinel-1 provides radar backscatter values (VV and VH), while Sentinel-2 contributes spectral indices like NDWI and NDVI, which help highlight water and vegetation. These features are then combined to create a unified dataset that captures both radar and optical information.The combined data is normalized to ensure all features are on the same scale, and redundant features are removed using feature selection techniques. Finally, the integrated dataset is used to train the flood detection model, such as RESNET-50, to identify flooded areas accurately.By integrating both datasets, the model benefits from a richer, more detailed understanding of the landscape, improving the accuracy and robustness of flood detection, even in challenging conditions.

IV. RESULTS

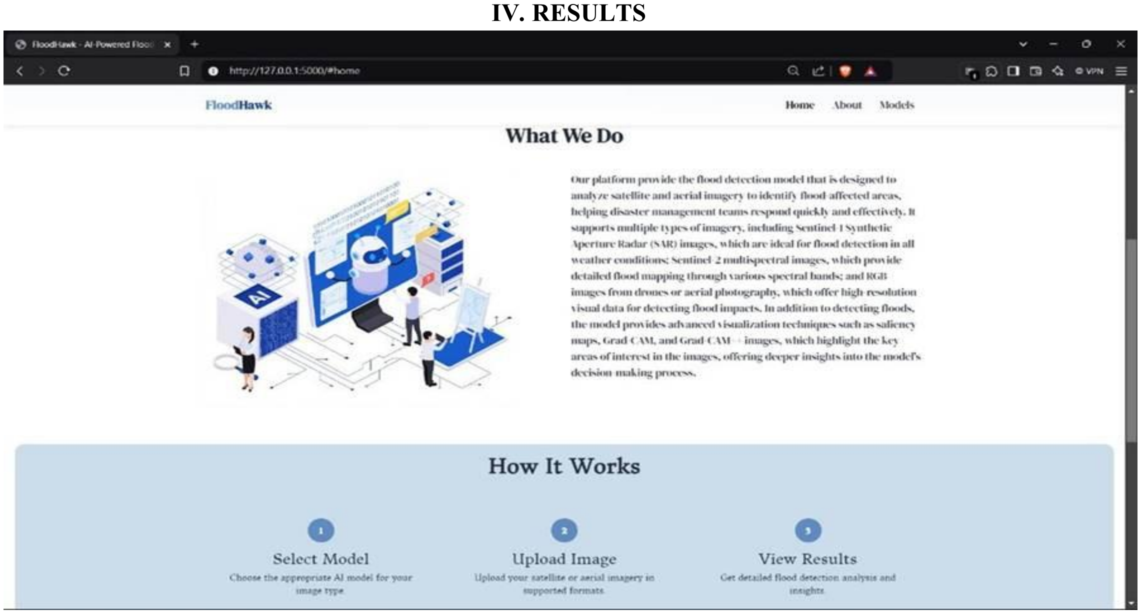

Fig 1.2 Results.

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V. CONCLUSION

FloodSee exemplifies the transformative potential of integrating advanced machine learning techniques with satellite imagery to address the critical need for automated flood detection. By combining the strengths of Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-2 optical data, the system effectively navigates challenges such as cloud cover, complex terrain, and dynamic environmental conditions, ensuring robust and reliable classification of flooded areas.Sentinel-1's SAR capabilities are especially advantageous for penetrating cloud cover and capturing data under all- weather conditions, while Sentinel-2's high-resolution optical imagery provides valuable complementary insights.At the heart of FloodSee lies a fine-tuned ResNet-50 model, a state-of-the-art convolutional neural network (CNN) architecture. The model has demonstrated exceptional performance, achieving remarkable accuracy and efficiency in distinguishing flood-affected regions from non-flooded areas. Its deep layers and residual connections allow for capturing intricate spatial patterns and features, making it well-suited for analyzing the diverse and often complex characteristics of satellite imagery. This project underscores the pivotal role of modern deep learning architectures in disaster management, showcasing their ability to process large volumes of multi-modal data efficiently. By integrating radar and optical data, FloodSee provides a comprehensive and scalable framework for real-time flood monitoring. Such innovation is crucial for improving disaster preparedness, enabling authorities to respond swiftly and effectively to flood events, thereby minimizing loss of life and property.

Challenges and Opportunities for Future Development

While FloodSee marks a significant step forward, challenges remain. Data availability, particularly for regions with limited satellite coverage or historical records, can hinder the system's global applicability. Additionally, the computational resources required for processing high-resolution satellite data and training deep learning models are non-trivial. Addressing these challenges will require strategic investment in data infrastructure, cloud computing, and partnerships with space agencies and technology providers.

Looking ahead, the FloodSee framework offers exciting avenues for further development:

1. **Temporal Analysis**: Incorporating time-series data can improve the system's ability to track flood progression, assess duration, and understand the temporal dynamics of affected regions.
2. **Integration of Additional Data Modalities**: Expanding the framework to include elevation models, meteorological data, and socioeconomic layers can enhance predictive accuracy and support more targeted disaster response strategies.
3. **Real-Time Optimization**: Streamlining the system for real-time deployment on cloud platforms or edge devices will enable near-instantaneous flood detection and updates, a critical capability for emergency management.

Impact on Disaster Preparedness and Response

FloodSee stands as a testament to the power of interdisciplinary innovation, blending advances in satellite remote sensing, machine learning, and geospatial analysis. By providing a reliable and scalable solution for automated flood detection, the system has the potential to revolutionize disaster management practices globally. Continued innovation and collaboration will be essential to fully realize its capabilities and extend its impact, making FloodSee a cornerstone of resilient and proactive disaster preparedness strategies.

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