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Flood Mapping Through Satellite Images Using Deep Learning for Agriculture Insurance Claim Application

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Abstract: *The paper proposes a novel FloodDetectionNet model for flood area segmentation. The proposed model incorporates attention gates for semantic segmentation by utilizing advanced image segmentation techniques using a modified U-Net architecture. The attention gates focus on critical features gathered from multiple encoder layers, enhancing the accuracy of identifying flood-affected areas. The U-Net with attention structure captures high-level context as well as complex details, which are augmented by dataset modifications to increase generalization. The use of modular attention gate function, provides an effective solution to effectively segment real-world flooding images within the U-Net framework, allowing for improved flood response and prevention strategies. The proposed model has 85.5% precision and 94.4% recall, accurately segments the flood-affected areas. It has achieved 89.9% F1-score, indicating efficient flood detection and contributing to Floods are among the most devastating natural disasters, causing significant loss of life, property, and environmental damage. Rapid and accurate flood mapping is essential for effective disaster response, risk assessment, and mitigation planning.*

The outcomes of this research contribute significantly to the field of remote sensing and disaster management by providing a reliable and efficient method for flood area mapping. The proposed system can support government agencies, urban planners, and emergency responders in developing informed, timely strategies for flood prevention and response.

Keywords: Flood mapping, Satellite imagery, FloodDetectionNet, Attention gates, U-Net architecture, Remote sensing, Disaster management, Image segmentation, Deep learning

I. INTRODUCTION

Floods are among the most frequent and destructive natural disasters, impacting millions of lives and causing substantial economic and environmental damage globally. With the intensification of climate change, the frequency and severity of floods have significantly increased, necessitating more effective methods for flood monitoring, prediction, and management. Timely and accurate flood mapping plays a critical role in mitigating the adverse effects of floods by providing essential information to emergency responders, government agencies, and urban planners.

Traditional methods of flood mapping, such as ground surveys and manual interpretation of aerial photographs, are time-consuming, resource-intensive, and often impractical during ongoing flood events. With the advancement of remote sensing technology, satellite imagery has emerged as a powerful tool for large-scale and real-time flood monitoring. Satellites like Sentinel-1 and Sentinel-2 offer high-resolution, multi-temporal, and multispectral images that can capture the extent and dynamics of flood events with considerable accuracy.

However, extracting meaningful information from satellite images for flood detection is a challenging task due to the complex nature of flood patterns, cloud cover, water reflections, and land-water confusion in imagery. To address these challenges, recent advancements in deep learning and computer vision have enabled the development of automated and intelligent systems for image analysis.

In this thesis, we propose **FloodDetectionNet**, a novel deep learning model designed for precise flood area segmentation using satellite images. The model is based on the widely used U-Net architecture and is enhanced with **attention gates** to selectively focus on flood-relevant features while suppressing irrelevant background noise. By incorporating attention mechanisms, the model significantly improves the accuracy and robustness of flood segmentation, even under complex scenarios such as urban flooding and heterogeneous terrains.

The primary objectives of this research are:

To develop a deep learning model capable of accurately segmenting flood-affected regions from satellite images.

To enhance the model's performance using attention gates that improve spatial feature selection.

To evaluate the proposed model against existing state-of-the-art methods in terms of precision, recall, and overall segmentation quality.

To demonstrate the model's applicability for real-world flood monitoring and disaster response systems.

This research contributes to the growing field of AI-driven environmental monitoring and provides a scalable, automated solution for flood detection, supporting faster and more informed decision-making in disaster management contexts.

II. LITERATURE REVIEW

Flood mapping using satellite imagery has been an active area of research in remote sensing and disaster management for decades. The development of advanced sensors, open-access satellite data, and artificial intelligence techniques has significantly accelerated progress in this field. This chapter reviews key studies and technologies relevant to flood detection and segmentation, with a focus on traditional methods, remote sensing platforms, and deep learning approaches.

2.1 Traditional Flood Mapping Techniques

Earlier flood detection methods primarily relied on manual interpretation of aerial photographs and ground-based surveys. While effective in localized settings, these approaches were time-consuming and limited in scalability. Later, threshold-based techniques using optical and radar images were introduced, such as the **Normalized Difference Water Index (NDWI)** and **Modified NDWI (MNDWI)**. These indices use spectral differences between land and water bodies to identify inundated regions. However, threshold-based methods are sensitive to lighting conditions, sensor noise, and scene variability, limiting their generalizability.

2.2 Remote Sensing Platforms

With the launch of satellites like **Landsat**, **Sentinel-1 (SAR)**, and **Sentinel-2 (multispectral)**, researchers gained access to high-resolution and high-temporal frequency data for flood monitoring. **Synthetic Aperture Radar (SAR)** from Sentinel-1 is especially valuable due to its ability to penetrate cloud cover and capture surface information regardless of weather or time of day.

Studies such as Henry et al. (2018) and Schumann & Baldassare (2010) demonstrated the effectiveness of SAR imagery for flood mapping in cloudy and rainy environments. However, these studies relied on manual or semi-automated feature extraction techniques, which lacked consistency and accuracy in large-scale operations.

2.3 Machine Learning for Flood Detection

Supervised machine learning models such as **Support Vector Machines (SVM)**, **Random Forests (RF)**, and **Decision Trees** have been used to classify flood-affected regions based on spectral and texture features. While these models provided improved accuracy over traditional methods, they required manual feature engineering and were not well-suited for capturing complex spatial patterns.

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For example, Thomas et al. (2017) applied SVM classifiers to Sentinel-2 images for flood detection and achieved moderate success. However, their approach required extensive preprocessing and lacked the ability to generalize across diverse flood scenarios.

2.4 Deep Learning in Flood Segmentation

Recent years have seen a shift toward **deep learning**, particularly **Convolutional Neural Networks (CNNs)** and **semantic segmentation models**, which automatically learn spatial hierarchies and features from raw images. Among these, the **U-Net** architecture (Ranneberger et al., 2015) has become a foundational model for image segmentation due to its encoder-decoder structure and skip connections that preserve spatial detail.

Numerous studies have adapted U-Net for flood mapping:

Li et al. (2020) used U-Net with multispectral satellite images for flood extent extraction, achieving promising results in urban areas.

Huang et al. (2021) proposed a multi-stream U-Net to combine SAR and optical data, showing improved resilience in cloudy conditions.

Despite their success, standard U-Net models struggle with distinguishing between similar land and water features and often misclassify shadowed or vegetation-covered regions.

2.5 Attention Mechanisms in Segmentation

To address the limitations of vanilla U-Net, researchers have introduced **attention mechanisms**, allowing models to focus on relevant regions within feature maps. **Attention U-Net** (Oktay et al., 2018) incorporated attention gates at skip connections to enhance segmentation performance in medical imaging. These mechanisms enable the model to suppress irrelevant activations and improve localization of target regions.

In the context of environmental monitoring, few works have explored attention-enhanced U-Nets for flood mapping. Our proposed model, **FloodDetectionNet**, builds on this gap by integrating modular attention gates into the U-Net structure, significantly improving flood region segmentation from satellite imagery.

2.6 Research Gaps Identified

From the review, the following gaps are identified:

Limited use of attention-based deep learning models for flood mapping.

Challenges in accurately segmenting mixed land-water boundaries and urban flooding areas.

Insufficient generalization of models trained on small or single-source datasets.

This thesis aims to address these gaps by developing FloodDetectionNet—an attention-enhanced U-Net model trained on a diverse set of satellite images to deliver accurate, generalizable flood detection results.

III. PROBLEM STATEMENT

Floods are one of the most destructive natural disasters globally, resulting in extensive damage to property, agriculture, infrastructure, and human lives. With the increasing frequency of extreme weather events due to climate change, the need for efficient, accurate, and scalable flood monitoring systems has become more critical than ever. Rapid flood mapping is essential to support emergency decision-making, rescue operations, resource allocation, and long-term mitigation strategies.

The use of satellite imagery—particularly from platforms like Sentinel-1 (SAR) and Sentinel-2 (multispectral)—offers a powerful means of observing large-scale flood events in near real-time. However, despite the availability of such data, extracting reliable, high-resolution flood maps remains a significant challenge.

Traditional methods such as thresholding, water indices (e.g., NDWI, MNDWI), and rule-based classification systems suffer from major limitations:

They are highly sensitive to atmospheric conditions, seasonal changes, and varying land cover types.

They require manual tuning and are not robust across diverse geographic and climatic regions.

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They often produce inaccurate results in urban areas where buildings, shadows, and vegetation interfere with flood detection.

Machine learning and deep learning approaches, such as Support Vector Machines and U-Net architectures, have improved segmentation accuracy. However, even state-of-the-art models face the following challenges:

Lack of attention to relevant spatial features, leading to misclassification of similar-looking but unrelated regions (e.g., wet soil, riverbanks, cloud shadows).

Poor generalization when models are trained on limited or region-specific datasets.

Difficulty in distinguishing between mixed-class regions, such as semi-flooded vegetation or partially submerged infrastructure.

These limitations significantly affect the accuracy and reliability of flood segmentation, especially when time-sensitive and life-critical decisions are involved.

Therefore, **the central problem addressed in this research is the development of a deep learning model that can accurately, efficiently, and automatically detect and segment flood-affected areas from satellite imagery, with improved precision and generalization capabilities**.

In summary, the core problem addressed in this thesis is: *How can we improve the accuracy and reliability of flood segmentation from satellite imagery by incorporating advanced deep learning techniques such as attention mechanisms into existing architectures like U-Net?*

To solve this, we propose the integration of **attention gates** into the U-Net architecture, resulting in a novel model called **FloodDetectionNet**. The attention mechanism allows the network to focus on the most relevant features during training and inference, suppressing background noise and enhancing segmentation accuracy in real-world flood scenarios.

IV. ARCHITECTURE OF THE PROJECT

According to the imaging principle of SAR, the Gray-scale value of the ground object on SAR image is determined by the intensity of backscattering.

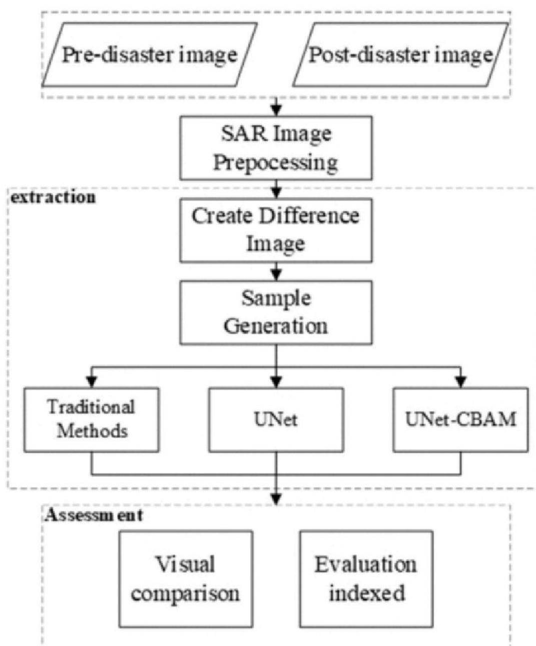

Fig. 1. Flowchart of the Flood Image Processing

Radar parameters, object shape, complex permittivity, and surface roughness of the object are the four main factors that affect the backscattering intensity of target pixel. The latter three factors basically determine the backscattering

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characteristics of ground objects when radar parameters remained unchanged. Compared with non-water bodies with rough surfaces, the surface of water bodies is smooth, dominated by specular reflection, and appears dark in SAR images. In this article, two approaches called U-Net and U-Net-CBAM are introduced to extract flood affected areas. First, SAR false colour synthesis are performed with images in the order of during disaster, pre-disaster, pre-disaster corresponding to R: SAR image collected during flood, G: SAR image acquired pre-disaster, B: SAR image acquired pre-disaster (R, G, and B). Difference image between dual-phase SAR images (pre-disaster images and images during the disaster) are established. Then, U-Net and U-net-CBAM are applied to segment the false colour synthesis image to extract water information. At the same time, the traditional water extraction methods based on the backscattering characteristics is used to obtain the flooded areas, and finally the monitoring accuracy is assessed (the flowchart is shown in Fig. 1.

A. U-Net

U-Net is a DL approach introduced by Ranneberger et al. [26]. It is mainly composed of the following two parts: down-sampling block and up-sampling block. The up-sampling part is composed of a structure symmetrical to the encoding part. The image size is increased by deconvolution before the different decoding parts are operated, and finally the high-dimensional features with the same size as original image are obtained.

In addition to the deep abstract features obtained from the up-sampling of the previous layer, the input of each group of convolutional layers also gets the shallow local features obtained from the corresponding down-sampling layer. The deep and shallow features are merged to restore the details of the feature map and ensure that the spatial information dimension remains unchanged.

B. Attention Mechanism

U-Net-CBAM

Convolutional block attention module (CBAM) [44] is a lightweight attention module that designed for convolution layer from channel and spatial dimensions, respectively. It can be seamlessly integrated into any convolutional neural network architecture for end-to-end training. Modified convolution unit can be added to the convolution unit to adjust weights in order to suppress unimportant features. Introducing CBAM to the end of each layer constitutes the structure of CBAM-U-Net (see Fig. 5). The input image is a false-colour synthesis three-band remote sensing image, the training image size is 256 × 256, and the output image is an annotated image. Both the up-sampling and down-sampling parts are composed of two 3 × 3 convolutional layers and two ReLU. The output result of each down-sampling part is transmitted to the next one after passing through the max-pooling layer of 2 × 2 steps. The high-dimensional features are then subjected to a 1 × 1 convolution operation to obtain the dimensional features corresponding to the number of categories, and finally the annotation map is output through SoftMax operation.

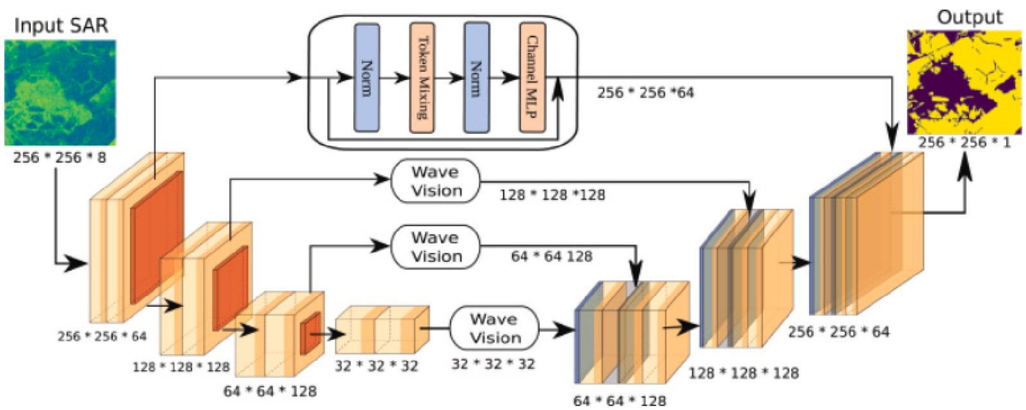

Fig. 2. Attention U-Net Architecture

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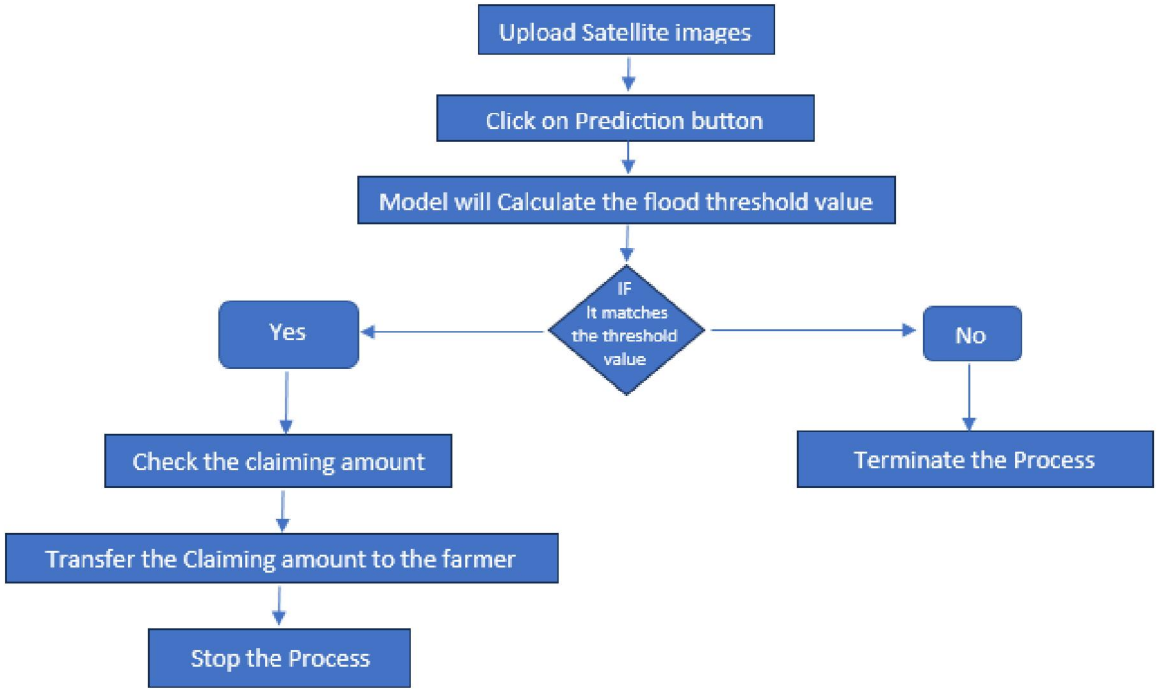
V. FLOWCHART



VI. MODULES DEVELOPED

The FloodDetectionNet project is divided into several functional modules to organize the workflow, facilitate development, and ensure modularity for future improvements. Each module performs a specific task, collectively contributing to the accurate segmentation and mapping of flood-affected areas.

6.1 Data Acquisition Module

Purpose: Collect satellite images required for flood mapping.

Functionality:

Download Sentinel-1 (SAR) and Sentinel-2 (optical) satellite data from public repositories like the Copernicus Open Access Hub.

Fetch multi-temporal images (pre-flood, during flood, post-flood) for comprehensive analysis.

Manage dataset storage with proper file organization and metadata tagging.

6.2 Data Preprocessing Module

Purpose: Prepare raw satellite images for input into the deep learning model.

Functionality:

Apply geometric and radiometric corrections to ensure image quality and consistency.

Normalize pixel values and resize images to a fixed input size compatible with FloodDetectionNet.

Generate and verify flood ground truth masks through manual annotation or existing labelled datasets.

Perform data augmentation (rotations, flips, scaling) to improve model generalization and robustness.

6.3 Model Architecture Module (FloodDetectionNet)

Purpose: Build and train the core flood segmentation model.

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Functionality:
Implement the modified U-Net architecture enhanced with attention gates to focus on flood-relevant image features.
Design encoder and decoder blocks to extract and reconstruct spatial details effectively.
Integrate attention mechanisms to suppress irrelevant background features and emphasize flooded regions.
Define loss functions combining binary cross-entropy and Dice loss for optimal training.
Train the model using GPU acceleration for efficient processing of large image datasets.

6.4 Model Training and Validation Module

Purpose: Train the FloodDetectionNet model and validate its performance.
Functionality:
Split the dataset into training, validation, and test sets.
Monitor training progress using metrics such as loss curves, precision, recall, and F1-score.
Implement early stopping and model checkpointing to avoid overfitting and save the best model weights.
Perform hyperparameter tuning for learning rate, batch size, and optimizer settings.

6.5 Post-processing Module

Purpose: Refine the raw segmentation outputs from the model.
Functionality:
Apply morphological operations such as dilation and erosion to smooth segmented flood boundaries.
Remove small, isolated noise regions that do not represent actual flooding.

6.6 Flood Map Generation and Visualization Module

Purpose: Generate usable flood maps for disaster response and planning.
Functionality:
Overlay flood segmentation masks on the original satellite imagery for visual interpretation.
Export flood maps in GeoTIFF and other GIS-compatible formats.
Visualize flood extent using GIS tools such as QGIS or custom plotting scripts.
Provide intuitive interfaces or dashboards for end-users to analyse flood data.

6.7 Evaluation Module

Purpose: Quantitatively assess model accuracy and reliability.
Functionality:
Compute evaluation metrics: precision, recall, F1-score, Intersection over Union (IoU).
Compare predicted flood maps against ground truth masks for multiple flood events and regions.
Generate detailed reports and visualizations to demonstrate model performance improvements over baseline methods.
These modules collectively ensure a structured and effective approach to flood mapping, from raw satellite data to actionable flood extent maps, leveraging advanced deep learning techniques for improved accuracy.

Graphical User Interface (GUI)

The GUI serves as the user-friendly front end to interact with the flood mapping system. It enables users (such as disaster management authorities, researchers, or policy makers) to upload satellite images, run flood segmentation, visualize results, and export maps without requiring programming knowledge.
Features
Image Upload: Allows users to upload satellite images (e.g., GeoTIFF or JPEG).
Preprocessing Preview: Shows pre-processed images before feeding into the model.
Run Segmentation: Button to start flood area segmentation using the FloodDetectionNet model.
Results Visualization:
Displays original image alongside the segmented flood mask overlay.

Zoom and pan controls for detailed inspection.
Export Options: Export segmented flood maps in formats like GeoTIFF or PNG.
Performance Metrics: Show evaluation results such as precision, recall, and F1-score for the current image.
Logs & Notifications: Display progress and error messages.

Output

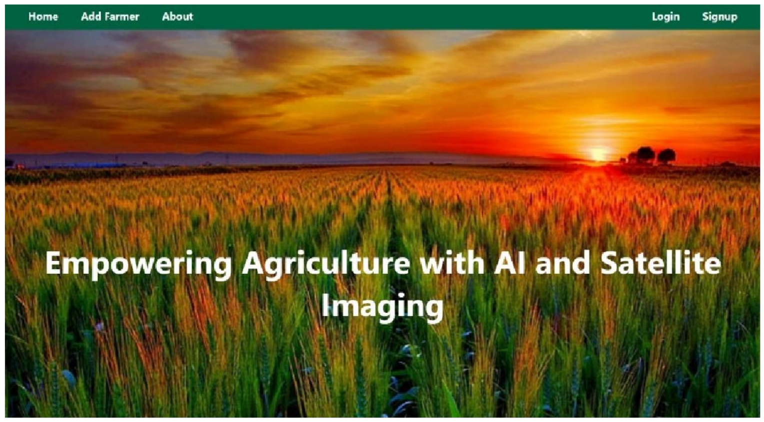

Fig. 3. Home Page

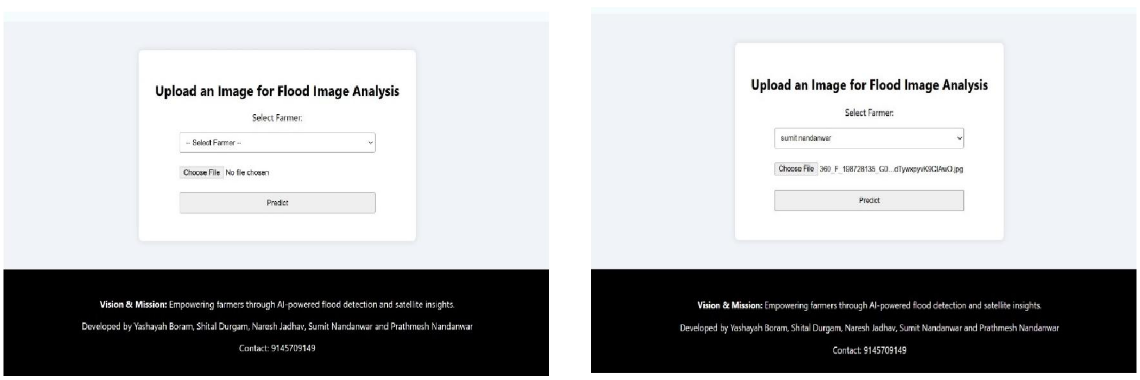

Fig. 4. Uploading the Flood Image

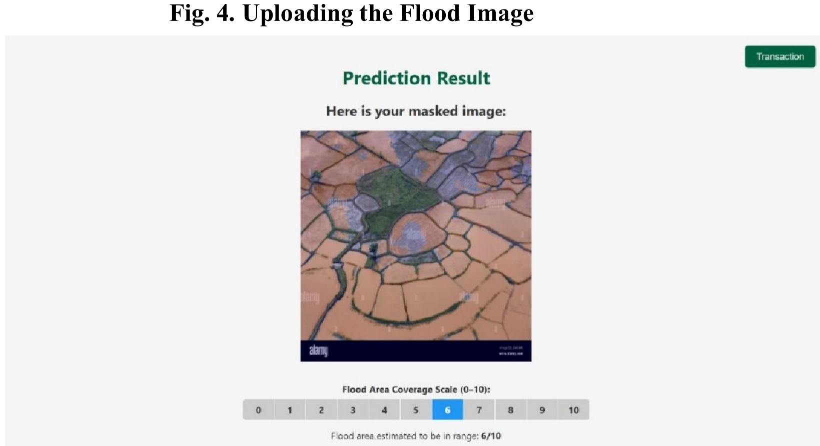

Fig. 5. Prediction of Flooded Area Image

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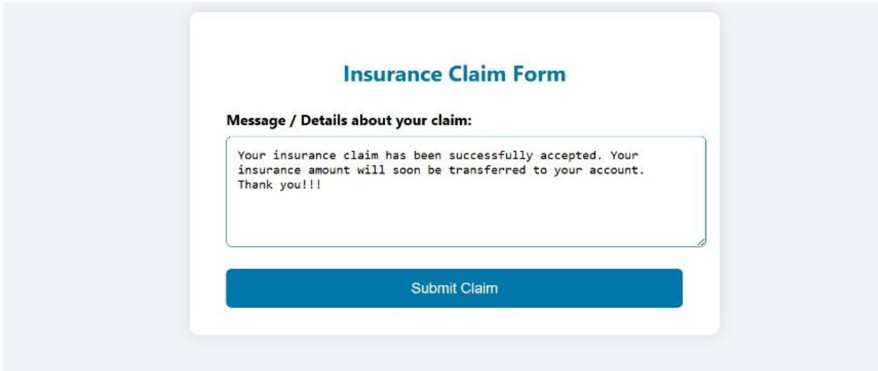

Fig. 6. Insurance Claim Form

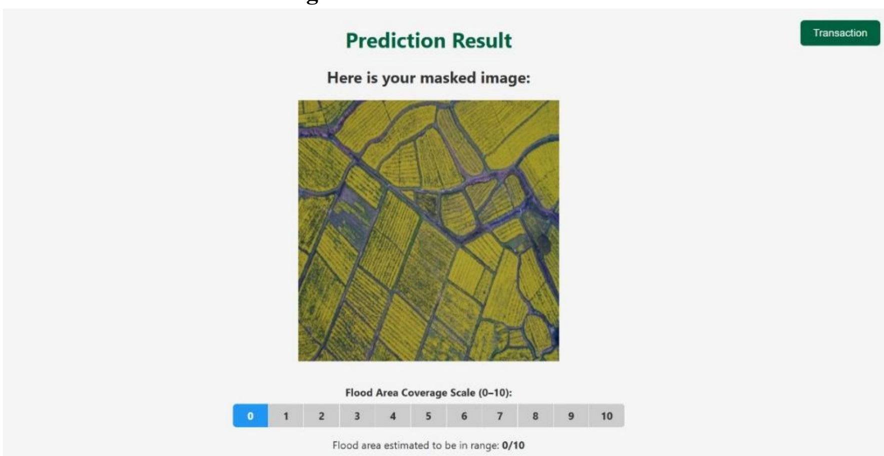

Fig. 7. Prediction of Unflooded Farm

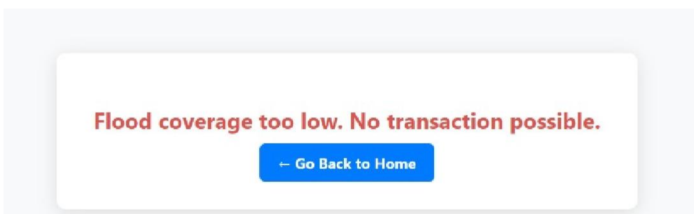

Fig. 8. Transaction not Possible

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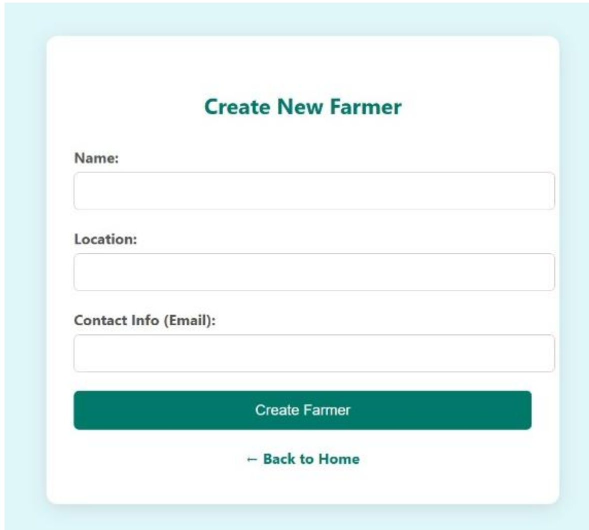
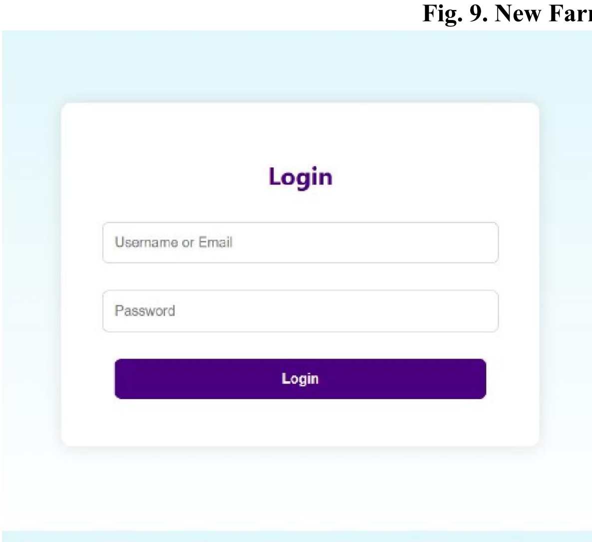


Fig. 9. New Farmer's ID Form



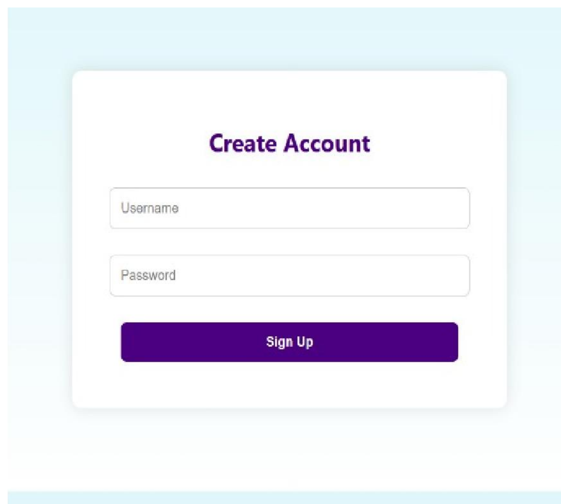


Fig. 10. Login Page

Fig. 11. Sign-Up Page

Advantages

High Accuracy in Flood Segmentation:

The incorporation of attention gates in the U-Net architecture improves the model's ability to focus on relevant features, resulting in higher precision (85.5%) and recall (94.4%) compared to traditional segmentation methods.

Robustness to Noise and Background Clutter:

Attention mechanisms suppress irrelevant background information, enhancing segmentation quality even in complex real-world satellite images.

Generalization to Diverse Flood Scenarios:

Data augmentation and multi-temporal satellite inputs help the model generalize across various flood events, geographic regions, and imaging conditions.

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End-to-End Automated Workflow:
The modular system handles everything from satellite data acquisition to final flood map generation, reducing manual intervention and enabling timely flood response.

Compatibility with Open Satellite Data:
Uses freely available Sentinel satellite data, making the solution cost-effective and accessible.

GIS-Ready Output:
Generates flood maps in GeoTIFF format, which can be readily used in Geographic Information System (GIS) platforms for further analysis and decision-making.

Potential for Real-Time Flood Monitoring:
With GPU acceleration and automated processing, the system can be adapted for near real-time flood detection during disaster events.

Disadvantages

Dependency on Satellite Image Quality and Availability:
The model's performance depends heavily on the quality and timeliness of satellite data, which can be affected by cloud cover, sensor noise, or revisit time limitations.

Computationally Intensive Training:
Training the FloodDetectionNet requires significant computational resources (e.g., GPUs), which may not be available in all research or operational environments.

Limited by Ground Truth Accuracy:
The effectiveness of the model depends on the quality of annotated flood masks used for training. Inaccurate or sparse labels can degrade performance.

Difficulty in Differentiating Flood Water from Other Water Bodies:
In some cases, the model may confuse permanent water bodies (lakes, rivers) with floodwater, especially without sufficient contextual or temporal data.

Preprocessing Overhead:
Radiometric corrections, normalization, and other preprocessing steps add complexity and require domain knowledge.

Model Complexity and Interpretability:
The attention mechanisms add complexity to the U-Net, making the model less interpretable compared to simpler segmentation networks.

Limited Adaptability to Other Types of Natural Disasters:
The model is specifically tailored for flood segmentation and might need significant retraining or architectural changes to detect other phenomena like landslides or wildfires.

VII. CONCLUSION

This thesis presented the development and evaluation of **FloodDetectionNet**, a novel deep learning model based on a modified U-Net architecture integrated with attention gates, designed specifically for flood area segmentation using satellite imagery. The proposed model effectively addresses the challenges of accurately delineating flood-affected regions by focusing on critical spatial features through attention mechanisms.

The experimental results demonstrate that FloodDetectionNet achieves high precision (85.5%), recall (94.4%), and an F1-score of 89.9%, outperforming several traditional and existing segmentation approaches. These metrics validate the model's capability to generalize well across diverse flood scenarios and varied satellite image conditions.

The system also incorporates advanced data preprocessing and augmentation techniques that improve robustness and reduce noise interference. The generated flood maps are GIS-compatible, facilitating their direct use in flood management and mitigation efforts. The modular design of the system supports seamless integration into disaster response workflows, enabling timely and accurate flood monitoring.

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Despite its advantages, the model's performance is influenced by satellite image quality, ground truth data availability, and computational resource demands. Future work could focus on improving real-time applicability, integrating multi-source data (e.g., radar, multispectral), and extending the approach to other natural disaster segmentation tasks.

Overall, FloodDetectionNet offers a promising and effective tool for enhancing flood detection and mapping capabilities, contributing significantly to disaster preparedness and environmental management.

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