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# Flood Mapping Through Satellite Images Using Deep Learning

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**Abstract***:* *Flooding is a pervasive natural disaster that significantly impacts agriculture, infrastructure, and communities, particularly in rural and agricultural regions. Traditional methods of flood assessment and compensation are often manual, time-intensive, and prone to inaccuracies, resulting in delayed aid and inequitable resource distribution. With advancements in technology, satellite imagery and artificial intelligence (AI) provide new opportunities for real-time flood mapping and automated disaster response.*
*This project proposes a Real-Time Flood Mapping and Compensation System using the Attention U-Net deep learning model. Satellite imagery is analysed to detect and segment flood-affected regions with high precision. The Attention U-Net architecture enhances segmentation accuracy by focusing on the most relevant regions in the images while ignoring irrelevant or noisy areas, such as clouds or non-flooded landscapes. The system integrates geospatial data on land boundaries to assess flood severity for individual properties, enabling fair and data-driven compensation for affected landowners.*
*This project holds significant potential for transforming flood disaster management by reducing response times, fostering transparency, and empowering affected communities to recover more effectively. The integration of advanced AI and geospatial technologies marks a critical step toward mitigating the impacts of natural disasters in a rapidly changing climate.*

**Keywords:** Flood mapping, Deep learning, Semantic segmentation, Vision MLP, Attention U-Net

## I. INTRODUCTION

The **Attention U-Net** is an advanced deep learning architecture designed to improve image segmentation tasks by integrating an attention mechanism into the traditional U-Net architecture. Originally introduced for biomedical image segmentation, Attention U-Net has demonstrated its versatility across various domains, including satellite imagery analysis, where it excels in tasks like flood mapping, land cover classification, and disaster impact assessment.

### Key Features of Attention U-Net

**U-Net Base Architecture:**

- U-Net is a well-established convolutional neural network (CNN) designed for pixel-level image segmentation.
- It consists of an encoder-decoder structure:
  - The **encoder** extracts features using convolutional and down-sampling layers.
  - The **decoder** reconstructs the image using up-sampling layers and combines these features with the encoder via skip connections.

**Incorporation of Attention Mechanisms:**

- Attention gates (AGs) are added to the skip connections of the U-Net architecture.

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- These gates enable the model to focus on the most relevant regions of an image while ignoring irrelevant or noisy parts.
- This feature is especially useful in complex imagery, such as satellite data, where areas of interest (e.g., flooded regions) may be small or obscured by noise (e.g., clouds or shadows).

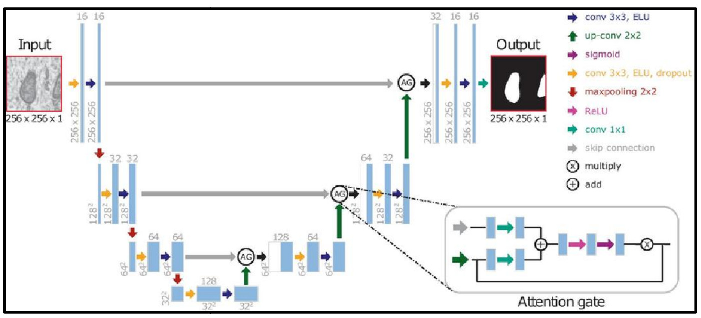
**Context Awareness:**

- Attention mechanisms allow the model to analyse the global context of an image, ensuring that segmentation decisions are more accurate and robust.

**Parameter Efficiency:**

- The use of attention gates minimizes redundant computations by selectively processing only the necessary regions, making the model computationally efficient for large-scale datasets.

**Fig. 1. Architecture of Attention U-NET**




## II. LITERATURE REVIEW

**1. Flood Mapping with Remote Sensing and GIS Techniques**

**Paper:** Smith, L. C. (1997). "Satellite remote sensing of river inundation area, stage, and discharge: A review." *Hydrological Processes.* This study highlighted the importance of remote sensing for hydrological disaster management, particularly flooding. It reviewed the capabilities of optical and radar sensors for flood mapping, emphasizing their potential to capture large-scale data efficiently. However, it noted limitations in manual interpretation and threshold-based approaches, which are prone to errors in complex environments. This paper laid the groundwork for automated flood detection using advanced computational techniques like machine learning.

**2. Application of U-Net for Image Segmentation**

**Paper:** Ronneberger, O., Fischer, P., & Brox, T. (2015). "U-Net: Convolutional Networks for Biomedical Image Segmentation." *Medical Image Computing and Computer-Assisted Intervention (MICCAI).* The U-Net architecture, originally developed for biomedical image segmentation, introduced a novel encoder-decoder structure with skip connections, making it highly effective for segmentation tasks. Its ability to perform well on small datasets while achieving high precision has made it a standard in environmental applications, including flood mapping. The study provides a foundational understanding of how U-Net can be adapted for satellite image analysis in flood detection.

**3. Attention U-Net for Flood Detection**

**Paper:** Oktay, O., et al. (2018). "Attention U-Net: Learning Where to Look for the Pancreas." *arXiv preprint arXiv:1804.03999.*Attention U-Net builds onthe U-Net architecture by integrating attentionmechanisms that focus on relevant parts of the image, enhancing segmentation accuracy. This is particularly useful for flood mapping, where distinguishing between water bodies and flooded areas can be challenging. The study demonstrated the model's ability to outperform traditional U-Net in segmentation tasks, making it suitable for scenarios like this project.

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**4. Flood Mapping Using Deep Learning and Sentinel-1 Data**

**Paper:** Huang, X., et al. (2020). "Deep learning-based flood mapping using Sentinel-1 SAR data." *ISPRS Journal of Photogrammetry and Remote Sensing.*

This study explored the use of Sentinel-1 synthetic aperture radar (SAR) data for flood extent mapping using deep learning. SAR data's capability to penetrate clouds and work in all weather conditions makes it ideal for flood analysis. The paper also highlighted challenges in data preprocessing and segmentation accuracy, demonstrating how deep learning models, including U-Net variants, can achieve reliable results.

**5. Automated Disaster Compensation Systems**

**Paper:** Wang, Z., et al. (2021). "Blockchain-based automated compensation mechanism for agricultural disasters." *Computers and Electronics in Agriculture.*

This study focused on integrating geospatial flood data with automated compensation mechanisms using blockchain technology. It emphasized fairness and transparency in compensation distribution, addressing traditional inefficiencies. Although the study targeted blockchain, its findings on data integration and financial transactions provide insights into developing a compensation framework for flood-affected areas in this project.

Building on this literature, the project combines cutting-edge image segmentation techniques with geospatial analysis and financial automation to provide a novel solution for flood mapping and compensation.

## III. PROBLEM STATEMENT

Flooding is one of the most devastating natural disasters, causing extensive damage to agriculture, infrastructure, and communities worldwide. Farmers and landowners are particularly vulnerable as flooding destroys crops, reduces soil fertility, and leads to significant financial losses. Current methods for assessing flood damage and providing compensation are often manual, time-consuming, and prone to inaccuracies, resulting in delays and inequitable aid distribution. These limitations exacerbate the economic and social impact of floods, hindering recovery efforts.

With the increasing frequency and intensity of floods due to climate change, there is an urgent need for a scalable, automated, and accurate solution to detect flood-affected areas and provide timely compensation to affected landowners. The integration of remote sensing data from satellite imagery with advanced deep learning techniques can address these challenges by enabling real-time flood detection and severity assessment. However, existing approaches either lack the precision required for effective flood mapping or fail to integrate a transparent compensation mechanism, leaving a critical gap in disaster management systems.

This project aims to bridge this gap by developing a **Real-Time Flood Mapping and Compensation System**. Leveraging satellite imagery, geospatial data, and the Attention U-Net model, the system will accurately segment flooded areas and calculate flood severity for individual properties. An automated compensation framework will ensure transparent and timely financial aid, enabling affected communities to recover more quickly and equitably.

Flooding is one of the most frequent and devastating natural disasters, causing significant losses in agriculture and impacting the livelihoods of millions of people. Farmers and landowners, especially in rural areas, often suffer severe damage to their crops and land due to unanticipated flooding, with limited means for quick recovery. Traditional methods for flood assessment and compensation can be slow and inefficient, relying on manual inspection and extensive paperwork, which often delay much-needed financial assistance. This lack of timely support makes it challenging for affected individuals to recover and restart their agricultural activities, amplifying the economic and social impact.

## IV. SEGMENTATION FRAMEWORK

The flowchart of the proposed methodology for flood mapping using dual polarized Sentinel-1 SAR imagery is illustrated in Fig. 1. Various polarization features are extracted from the dual-polarized Sentinel-1 SAR imagery. Python TensorFlow GPU 2.6.2 is used for deep learning model development and the performance of each segmentation architecture for flood mapping is assessed. More details on the procedures are discussed in the following sections.

Given a set of data (XSAR, Y), where XSAR represents the input Synthetic-Aperture Radar (SAR)backscattering coefficients for the segmentation model, and Y represents binary or flooding maps. Considering the Sentinel-1 SAR imagery, $XSAR \in Rw \times h \times bc$, where w and h represent spatial width and height, respectively, and $bc=\{2,\ldots,n\}$ is the number of input backscattering features (i.e., VV, VH, and the extracted backscattering features), the objective is to generate a segmentation map, $Y \in Rw \times h \times bc$, where $bc \in \{VV,VH\}$. This can be achieved by estimating the output of thepixel class using $Y=F(XSAR)$ for theinput XSAR having the same spatial size as $(w\times h)$. We have developed and introduced the Residual Wave Vision U-Net (WVResU-Net), as depicted in Fig. 2, which is an enhanced ResU-Net framework for the segmentation of flooding regions. The proposed WVResU-Net integrates the characteristics of vision MLPs in the form of a U-shaped ResU-Net architecture. There are several significant advantages to using the WVResU-Net: (1) The skip connections in a residual unit, which convey low-level features to their corresponding high-level feature representations, enhance the propagation of information without degradation. This enables us to build a lower-complexity segmentation model that gains more effective semantic segmentation knowledge with a limited quantity of labelled data. (2)The use of residual learning facilitates efficient network training. (3) The Wave Vision function treats each image patch as a wave operation with two essential key elements: amplitude and phase. Amplitude corresponds to the initial backscattering coefficients, while the phase is estimated as a complex value that varies relative to the semantic information of the input Sentinel-1 SAR backscattering features.

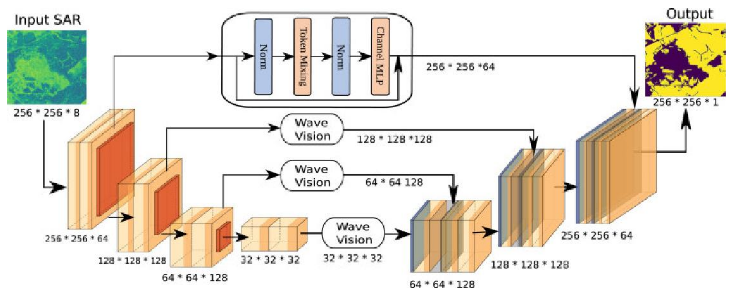


**Fig. 2. Overall design of the proposed Residual Weve Vision U-Net architecture**

## V. MODULES DEVELOPED

The proposed workflow introduces a streamlined, automated flood insurance or compensation system where the Attention U-Net model is used for flood mapping based on satellite imagery, combined with a user input system for land-specific analysis. When flooding is detected in the area exceeding a predefined threshold, the application initiates a transaction process (such as insurance payout or compensation). Here's how this could work step-by-step:

Detailed Workflow for Flood-Based Compensation System

**1. User Registration and Land Mapping**

- **Landowner Registration**: Landowners can register their property details in the application, including boundaries of their farmland, using geospatial coordinates or by selecting the area on an interactive map.
- **Boundary Mapping**: Upon registration, the system saves each property's geolocation and boundary coordinates in the database. This allows the model to focus specifically on each registered landowner's property during flood analysis.

**2. Satellite Imagery Acquisition and Pre-Processing**

- **Periodic Satellite Image Retrieval**: The application regularly retrieves satellite images for the areas of interest using APIs from satellite providers (e.g., Sentinel, Planet Labs, or Google Earth Engine).
- **Pre-Processing**: Each image is pre- processed (resized, normalized, etc.) to match the input requirements of the Attention U-Net model.
- **Region Selection**: Only the areas within each landowner's registered boundary are processed, optimizing computational resources and reducing processing time.

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**3. Flood Mapping with Attention U-Net**

- **Flood Detection**: The Attention U-Net model is used to analyse the satellite images, identifying and segmenting flooded areas.
- **Threshold Calculation**: The model calculates the percentage of the landowner's area affected by flooding. For instance, if 40% of a registered farm area is flooded, this percentage is saved as the "flood severity level."

**4. Automated Flood Severity Analysis**

- **Severity Thresholds:** The application checks the flood severity percentage against predefined thresholds **(e.g.,** 20%, 50%, etc.).
- **Decision Criteria**: If the detected flood level exceeds a critical threshold (e.g., 30%), the system determines that a transaction is warranted. The payout may be tiered based on severity:
- **20-50% Flooding**: Partial payout.
- **50-100% Flooding**: Full payout or higher-tier payout.

**5. Compensation Calculation**

- **Compensation Formula**: Based on the percentage of the land flooded, a compensation amount is calculated using a predefined formula. The formula might include:
  - Total insured value or expected yield of the land.
  - Percentage of flood severity.
  - Multiplier for specific land types or crop types if applicable.

**Sample Formula**:
text
Copy code
Compensation Amount = Insured Value * Flood Severity Percentage * Crop Yield Factor
6. **Transaction Execution**

- **Automated Payment Processing**: Once the compensation amount is calculated, an automated transaction is triggered. Payment processing can be done using integrated financial APIs like Stripe, PayPal, or through direct bank transfer APIs.
- **Notification to Landowner**: Landowners receive notifications detailing the assessed flood level, compensation amount, and payment status.

7. **User Feedback and Verification (Optional)**

- **Feedback Loop**: Landowners can verify the payout accuracy and provide feedback on the assessment, which can be used to adjust future models or update severity thresholds.
- **Audit Logs**: Each flood event and transaction is logged for transparency, which can be beneficial for insurance companies and regulatory audits.

Technologies for Building the Real-Time Transaction System

- **Backend Services**: Python (Flask, Django) or Node.js for API and backend services.
- **Database**: PostgreSQL, MongoDB, or a spatial database like PostGIS to store geolocation data and flood mapping results.
- **Mapping and Visualization**: Mapbox, Leaflet, or Google Maps to display flooded areas on the web or mobile interface.
- **Machine Learning Framework**: TensorFlow or PyTorch for model deployment and inference.
- **Payment Gateway**: Stripe, PayPal, or bank API for automatic transaction processing.
- **Notification Service**: Twilio, Firebase Cloud Messaging, or email services for alerting landowners.

## VI. ADVANTAGES

**1. Enhanced Focus on Relevant Regions**

- The attention mechanism in Attention U-Net allows the model to focus on the most relevant parts of the satellite images, such as flood-affected areas, while ignoring irrelevant regions like clouds or unaffected landscapes.
- This ensures higher accuracy in segmenting flooded regions.

**2. Improved Accuracy**

- Compared to the standard U-Net, the Attention U-Net achieves better segmentation performance, especially in complex scenarios where flood boundaries are difficult to distinguish.
- Metrics like Intersection over Union (IoU) and Dice Score are significantly improved.

**3. Handles Data Imbalance**

- Flooded areas often occupy a smaller portion of the image compared to non-flooded regions. The attention mechanism helps the model handle this imbalance effectively by prioritizing flooded areas during training and inference.

**4. Scalability**

- Attention U-Net can be adapted to different types of satellite images (e.g., optical, radar) and resolutions, making it suitable for various datasets and regions.

**5. Integration of Multiscale Features**

- The skip connections and attention gates enable the model to combine features from different scales, which is crucial for accurately identifying both large and small flooded areas.

**6. Automation and Efficiency**

- Automating the segmentation process significantly reduces the time and manual effort required for flood mapping, making it ideal for real-time applications.

## VII. DISADVANTAGES

**High Computational Requirements**

- Attention U-Net requires substantial computational resources, including high-end GPUs and sufficient memory, especially when processing high-resolution satellite images.
- This can limit its usability in resource-constrained environments.

**Complexity of Training**

- Training the Attention U-Net is more computationally intensive and time-consuming compared to the standard U-Net, as attention gates introduce additional parameters.
- Fine-tuning the model for different datasets requires expertise and experimentation.

**Data Dependency**

- The performance of the model heavily depends on the quality and diversity of the training data. Inconsistent or low-quality satellite images (e.g., due to cloud cover) can affect accuracy.

**Overfitting Risk**

- Due to the increased number of parameters introduced by the attention mechanism, there is a higher risk of overfitting, particularly when the training dataset is small.

**Interpretability Challenges**

- While the attention mechanism enhances performance, it can be difficult to interpret or explain the exact decision-making process of the model, especially for critical applications like disaster management.

**Deployment Challenges**

- Integrating Attention U-Net into a real-time flood detection and compensation system requires robust backend support and seamless data pipelines, which can be challenging to implement.

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## VIII. SEGMENTATION MAPS

Flood segmentation maps and confusion matrices as shown in Fig. 5, Fig. 6, Fig. 7, Fig. 8 illustrate that the developed segmentation algorithm of *WVResU-Net* resulted in the best segmentation performance for mapping flooded areas, while the over-segmentation of flooded regions was not significantly high. Interestingly, the *TransU-Net* model resulted in the least over-classification of flooded regions, but it struggled to recognize flooded regions accurately (i.e., it under-classified flooded pixels). The highest over-classification of flooded regions was observed in the results obtained by the *R2-UNet* algorithm, followed by the *TransU-Net++* model. The highest under-classification of the flooded area was seen in the results of the *U-Net+++* model, followed by the segmentation model of *TransU-Net*. In addition to the developed *WVResU-Net* model, the *TransU-Net++* and *SwinU-Net* segmentation algorithms resulted in the highest accuracy in identifying flooded pixels. The most interesting pattern observed in the results of segmentation was the better accuracy of the model based on vision transformers for accurate flood mapping compared to the CNN-based segmentation models. As discussed, CNNs have several significant disadvantages, one of which is that they can only predict whether a desired feature will appear in an image, not where it will be located. The sequential properties of the backscattering coefficients of SAR imagery cannot be precisely determined by CNNs due to their fundamental limitations in the backbone. The self-attention technique utilized in ViTs can effectively address this specific issue. It should be noted that under-classification can occur due to factors like wind, inundated vegetation, and rain, which can make open water regions appear as rough surfaces and alter the backscattering pattern. Conversely, low backscatter from smooth or dark urban surfaces, such as roofs, car parks, concrete, and asphalt, which may resemble water, can lead to over-classification. Furthermore, one of the greatest challenges in flood recognition is interpreting the backscatter responses of various targets within urban and vegetated regions based on the presence or absence of floodwater. For example, it was observed that the deep learning models, specifically CNN-based algorithms had difficulty in differentiating between inundated vegetation and urban areas due to similar backscattering pattern of these two features. The reason is that the double-bounce is the predominant backscattering mechanism in both inundated vegetation and urban areas. Nevertheless, intricate backscatter mechanisms caused by various kinds of buildings and heights, vegetation areas, and distinct road patterns make detecting floods in urban areas difficult for SAR.

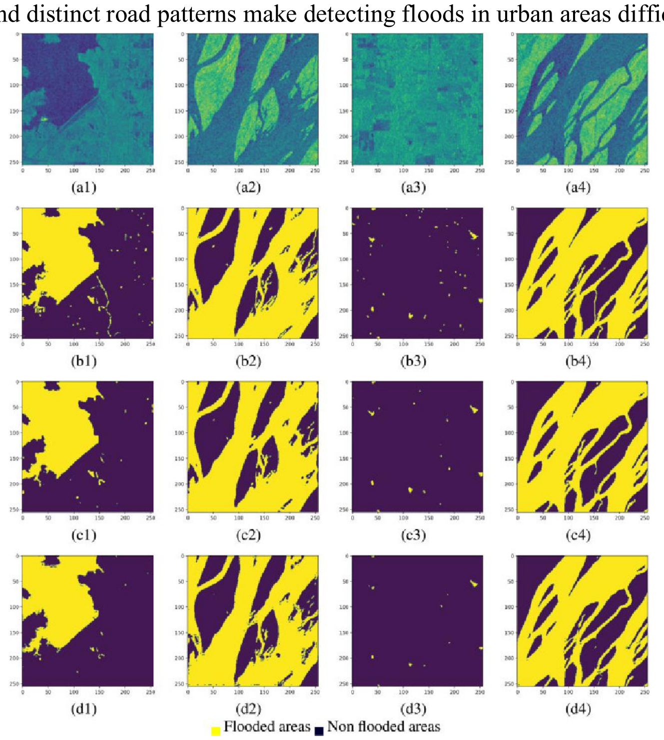


**Fig. 3. Segmentation maps of four randomly selected areas obtained using segmentation algorithms of (a1-a4) Sentinel-1 polarization data of VV, (b1-b4) flood masks, (c1-c4) U-Net+++ and (d1-d4) AttentionU-Net, respectively.**

## IX. CONCLUSION

Flooding remains a significant global challenge, with devastating impacts on agriculture, infrastructure, and livelihoods. Traditional methods of flood assessment and compensation are time-consuming, prone to inaccuracies, and often inequitable, leading to delays in recovery efforts. This project addresses these challenges by leveraging cutting-edge technologies in deep learning and geospatial analysis to develop a **real-time flood mapping and compensation system** By employing the **Attention U-Net** model, the system achieves precise flood segmentation from satellite imagery, enabling accurate detection of affected regions. Integrating this data with geospatial property boundaries allows the calculation of flood severity at an individual property level. The automated compensation mechanism ensures fairness and transparency, expediting financial aid to impacted landowners.

This interdisciplinary approach not only improves the speed and accuracy of disaster response but also fosters trust among stakeholders by offering a data-driven solution. The integration of satellite imagery, machine learning, and fintech highlights the potential of technology to address real-world problems, with further applications in disaster management, insurance, and government aid.

Moving forward, this project can be expanded to incorporate real-time monitoring systems, predictive analytics for flood forecasting, and scalable cloud-based deployments for global applicability. With continued advancements, the system can serve as a model for leveraging AI to enhance disaster resilience and recovery in vulnerable communities.

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