Advances in Nonlinear Variational Inequalities
ISSN: 1092-910X
Vol 28 No. 2s (2025)

Flood Detection Utilizing Sentinel-1 Synthetic Aperture Radar Data: A Comparative Analysis of U-Net and DeepLabV3 Architectures with Varied Encoder Configurations

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Article History:

Received: *18-09-2024*

Revised: *29-10-2024*

Accepted: *10-11-2024*

Abstract:

Flood detection is essential for mitigating the devastating impacts of natural disasters, especially in flood-prone regions where timely intervention can save lives and resources. This study proposes an innovative approach to flood detection. It leverages Synthetic Aperture Radar (SAR) imagery from Sentinel-1 satellites, which offers robust, all-weather monitoring for large geographic areas. This research paper explores the use of deep learning techniques to enhance the accuracy of flood detection using SAR data. The paper further performs comparative analysis of two state-of-the-art deep learning architectures namely U-Net and DeepLabV3, both of which are optimized for pixel-level segmentation tasks. By experimenting with varied encoder configurations, including ResNet, MobileNet, DenseNet and applying them to SAR data, this study evaluates the accuracy, precision, recall, and computational efficiency of each model in identifying flooded regions. The findings highlight critical differences in how these architectures and encoder configurations handle noisy radar data, offering insights into the most effective model-encoder combinations for flood detection. This research contributes to the advancement of automated flood monitoring systems and serves as a basis for further improvements in disaster response technologies.

Keywords: Flood Detection, Synthetic Aperture Radar (SAR), Sentinel-1, U-Net, DeepLabV3, Encoder Configurations, Image Segmentation, Disaster Monitoring, Remote Sensing, Deep Learning in Natural Disasters, Machine Learning, Python, Scikit-Learn, Keras, Data Visualization.

I. Introduction

Floods are among the most frequent and destructive natural disasters. This poses a significant threat to human life, infrastructure and economies worldwide. Accurate and timely flood detection is essential for effective disaster management, enabling authorities to take preventive measures and mitigate damage. However, traditional methods of flood monitoring, such as ground-based observations and optical satellite imagery face limitations due to their inability to operate under adverse weather conditions. Synthetic Aperture Radar (SAR) technology, particularly from satellites like Sentinel-1, overcomes these challenges by providing high-resolution and all-weather imaging capabilities. This makes it an ideal candidate for flood detection. Section II of the research paper dwells into the Literature survey . Building upon existing literature, we propose a flood detection and early warning system using machine and deep learning technologies. Section III and IV elaborate on the lacunas of the existing system and the proposed methodology respectively. Advanced flood detection system and its architecture is proposed in section V. Based on the dataset observed, various algorithms are implemented and represented in section VI of the paper. To add further, the paper focuses on the comparative analysis of U-Net and DeepLabV3, two popular segmentation architectures with varied encoder configurations such as ResNet, MobileNet and DenseNet. The performance of these models is further elaborated in terms of accuracy, precision, recall, and computational efficiency as a quantatitive measure. By focusing on the integration of advanced machine learning techniques with SAR data, qualitative measures of determining the effectiveness of flood monitoring systems are undertaken which contributes to more reliable disaster preparedness and response strategies. The paper concludes and specifies the future scope in section VII and VIII by providing improvements for flood detection and mitigation through the state of art technology contributing to early warning sytems.

II. LITERATURE SURVEY OF EXISTING SYSTEMS

Literature survey consists of understanding the natural disaster management system, the technologies involved and the various evaluation measures undertaken , as represented below. In the study by Hashi A.O. et al. [1], the authors focussed on developing a real-time flood detection system by combining machine learning with IoT technologies. The system collects real-time water level data via ultrasonic sensors and uses Random Forest algorithm to predict flood occurrences. Achieving an accuracy of 98.7%, the system proved to be highly effective for flood-prone regions. However, issues such as data imbalance were noted, which may bias the prediction, expressed the authors. The researchers suggested integrating video surveillance into future iterations for better flood intensity detection [1]. In another study, Mousa M. et al. [2] focused on flash flood detection in urban cities using ultrasonic sensors and Artificial Neural Networks (ANNs). Their system measured ambient temperature, humidity, and water levels. This information was combined and the data was processed through an ANN model. This led to the achievement of a low error rate. Despite its success, environmental factors like temperature affected the sensor's accuracy. The authors proposed utilizing more sophisticated neural networks and broader sensor data to enhance the model's performance [2]. Ghosh B. et al. [3] explored deep learning for flood detection in their 2024 study using U-Net-based models with Sentinel-1 SAR data. They aimed to automatically segment flooded areas from nonflooded regions, achieving over 96% accuracy. Challenges such as noisy environments and urban landscapes reduced the model’s effectiveness, prompting the need for multi-sensor data fusion for future improvements [3]. A review by Amitrano D. et al. [4] examined traditional and modern flood detection methods using SAR data. The research highlighted SAR’s consistent imaging under all weather conditions. It also pointed out complications caused by scattering in vegetated and urban areas. The review recommended the development of higher-resolution SAR missions to address these challenges and improve flood mapping precision [4]. Vanama VS. et al. [5] introduced the

GEE4FLOOD framework in 2020, leveraging Sentinel-1 SAR data and Google Earth Engine for rapid flood mapping. Using change detection algorithms, the framework achieved 82% accuracy in generating flood inundation maps. However, the use of Otsu's thresholding method led to inaccuracies in complex terrains. The study suggested exploring more sophisticated SAR processing techniques to improve map accuracy [5]. Continuing with remote sensing methods, the 2022 study by Munawar H.S. et al. [6] reviewed flood prediction techniques using multispectral, radar, and LiDAR data. The authors emphasized the potential of these methods for comprehensive flood risk assessments but noted limitations due to satellite orbital cycles, leading to spatial gaps. Future work aimed to integrate deep learning models to enhance real-time prediction accuracy [6]. The 2001 study by N. Baghdadi et al. [7] evaluated polarimetric C-band SAR data for wetlands mapping, using supervised classification. It distinguished between various land cover types, including water and urban areas. While C-band SAR's sensitivity to moisture was beneficial, certain wetland areas could not be clearly distinguished. This was due to similar backscatter characteristics. The authors recommended evaluating newer SAR missions for better classification accuracy [7]. Y Bai et al. [8] focused on distinguishing between permanent water bodies and temporary floodwaters. The authors focussed on using deep learning models with multi-source data fusion from Sentinel-1 SAR and Sentinel-2 optical imagery. The model achieved high accuracy for surface water detection. However, temporary water bodies posed classification challenges. Future research aimed to train segmentation models with high-resolution datasets for improved results [8]. In 2018, Dasgupta et al. [9] introduced a neuro-fuzzy flood mapping technique using SAR images. This method provided probabilistic flood maps and reduced errors compared to traditional texture-based techniques. However, the system's sensitivity to variations in SAR image texture posed challenges in some conditions. Future work seeked to refine texture-based methods for greater flood detection accuracy[9]. The 2021 study by G. Konapala et al. [10] explored the integration of Sentinel-1 SAR and Sentinel-2 optical imagery for flood inundation mapping using deep convolutional neural networks (CNNs) like U-Net. By combining SAR's all-weather capabilities with Sentinel-2's multi-band optical data, the study enhances flood detection performance. Despite achieving good results, challenges arose from poor contrast between flooded and non-flooded areas when using the VV and VH bands. Future work aimed to benchmark different deep learning architectures and incorporate digital elevation models (DEMs) to improve flood mapping in complex terrains [10]. In 2018, the work by Ouled Sghaeir et al. [11] focused on flood extent mapping using time-series SAR imagery and texture analysis. The study introduced a fusion method that leveraged structural similarity metrics and texture extraction. This helped mitigate the effects of speckle noise in SAR images. While robust, the technique struggled in areas with dense vegetation where SAR backscatter signals were weaker. The authors suggested that future research should integrate additional data sources, such as LiDAR and optical imagery, to improve flood detection in vegetated regions [11]. In an earlier contribution, the 2002 study by JB Henry et al. [12] examined the effectiveness of ENVISAT's Advanced Synthetic Aperture Radar (ASAR) for flood mapping. The study compared ASAR's various imaging modes, including Image Mode (IM) and Alternating Polarization (AP) Mode, to assess their capability for flood detection. It found that while VV polarization was not particularly effective in detecting floodwaters, multi-polarization data offered better performance. The study recommended enhancing the Earth observation data processing chain to improve operational flood mapping using ASAR [12]. D. Ritushree et al. [13] tackled flood detection in arid regions in 2023 by incorporating textural features from SAR images, improving the accuracy of flood delineation by 26%. However, challenges persisted with the use of VH polarization, which performed less effectively than other polarizations. The authors suggested further exploration of texture-based techniques to refine flood mapping in arid environments [13].

The literature survey thus revealed a rich variety of methods for flood detection, ranging from realtime monitoring using IoT and machine learning to advanced deep learning techniques applied to SAR data. Each study presented unique strengths, such as rapid processing and high accuracy, while also identifying specific limitations that provide avenues for future research. These studies collectively contributed to the ongoing improvement of flood detection systems. The aim was to reduce the devastating impacts of floods through timely and accurate interventions. Yet they failed to provide a combined solution to each paper's shortcomings i.e. either failing short on accuracy or either falling short on diversity or scope of places affected.

III. Limitations In Existing System

The challenges in existing flood detection systems are diverse and complex. One of the primary limitations is the dependence on specific data sources, such as Synthetic Aperture Radar (SAR) or optical imagery, without effectively integrating multi-sensor data fusion. This limits the robustness of models in diverse environments, such as vegetated or urban areas, where the backscatter signals from SAR alone may not sufficiently differentiate flooded regions. Additionally, many models faced challenges with class imbalance in the dataset, particularly in regions where floods occur infrequently. This imbalance can skew model training, leading to biased predictions and lower accuracy in less-represented flood scenarios.

Another issue is the lack of standardization in model architectures and hyperparameter tuning across studies. This made it difficult to replicate results or compare the performance of different approaches. Furthermore, many flood detection systems rely on a single type of imagery (e.g., SAR), which may perform poorly under certain conditions like low contrast between water and land or in highly dynamic environments. This over-reliance on a single data source limited the adaptability of these models to different flood conditions.

Moreover, existing methods often struggle with noisy data, particularly in environments where radar signals are affected by scattering in vegetated or urban regions. Many systems do not account for this adequately, resulting in higher error rates during flood delineation. The limitations of traditional thresholding techniques, such as Otsu's method, further complicated flood detection by failing to provide accurate segmentation in complex terrains.

Computational inefficiency was also a major concern. Real-time flood detection is critical for disaster management, but many current systems are not optimized for rapid processing. This delays flood mapping, limiting their applicability in time-sensitive scenarios. Additionally, some methods face challenges in handling large-scale geographic areas, often due to limitations in satellite orbital cycles, which lead to gaps in spatial coverage.

Transparency in reporting model details, including preprocessing steps, training processes, and evaluation metrics, is often insufficient. This lack of clarity hampers replicability and prevents researchers from building on prior work effectively. Future improvements should focus on addressing these issues through better data fusion techniques, enhanced processing capabilities, and more transparent methodologies to ensure that flood detection systems can perform reliably across different environmental conditions.

IV. PROPOSED SYSTEM

The objective of this paper is to develop an advanced flood detection system utilizing deep learning models on Synthetic Aperture Radar (SAR) imagery. This system aims to compare the accuracy and efficiency of U-Net and DeepLabV3 models, particularly in regions vulnerable to flooding. By incorporating several key components for precise pixel-level segmentation and environmental monitoring, the work seeks to enhance the overall effectiveness of flood detection efforts.

1. Flood Detection Using U-Net and DeepLabV3:

The proposed system leverages two state-of-the-art deep learning architectures, U-Net and DeepLabV3, which are optimized for pixel-level segmentation. These models are applied to Sentinel-1 SAR imagery to identify flooded areas with high precision. The use of U-Net and DeepLabV3 allows for detailed flood mapping, which is critical for timely disaster response and resource allocation. These models are particularly well-suited for handling the complex nature of SAR data, which often includes noise from radar backscatter in challenging environments.

2.Encoder Configurations (ResNet, MobileNet, DenseNet):

To enhance segmentation performance, we used various encoder configurations with U-Net (ResNet34, MobileNetV2, DenseNet121) and DeepLabV3 (ResNet101, MobileNetV2). A comparative analysis was conducted to evaluate the accuracy, precision, recall, and computational efficiency of each encoder-model combination, helping identify the most effective setup for flood detection using SAR imagery. This ensures adaptability across different environmental conditions.

3.Utilization of Sentinel-1 SAR Data:

Sentinel-1 SAR data forms the core of our flood detection system. It provides consistent, all-weather, day-and-night monitoring capabilities. This makes it particularly advantageous for real-time flood detection, even in adverse weather conditions where optical imagery may be limited. The SAR data's ability to penetrate cloud cover and capture high-resolution imagery ensures that the system can reliably detect floods, thus improving the overall effectiveness and timeliness of the flood response.

4.Comparative Evaluation of Model Performance:

A key component of the proposed system is the comparative evaluation of U-Net and DeepLabV3 models across different encoder configurations. The performance of each model-encoder combination is assessed using various metrics such as accuracy, precision, recall, and F1 score. This comprehensive evaluation provides insights into the relative strengths of each architecture when applied to SAR imagery. The results will inform the selection of the most effective model for flood detection applications.

5.Scalability and Future Enhancements:

The system is designed to be scalable, with potential to cover larger geographic areas and integrate with additional environmental monitoring systems. Future enhancements will focus on integrating the detection results with interactive maps, enabling disaster management authorities to better visualize and understand the extent of affected areas. The integration of multi-sensor data fusion, combining SAR with optical imagery, will also be explored to improve detection accuracy. Additionally, real-time flood detection capabilities will be investigated to increase the system's utility during active flood events.

In this study, we have performed a comparative analysis of U-Net and DeepLabV3 architectures for flood detection using SAR imagery, leveraging different encoder configurations to optimize segmentation accuracy. The use of SAR data ensures consistent flood detection, even in challenging weather conditions. Future work will focus on enhancing the system with map-based visualizations of flood-affected areas and exploring real-time monitoring capabilities. This study lays the groundwork for a scalable, effective tool in flood detection and disaster management.

V. PROJECT ARCHITECTURE

The architecture of our flood detection system using Sentinel-1 SAR imagery, as represented in Fig.1 is structured into several critical stages, each contributing to the accurate detection of flooded areas.

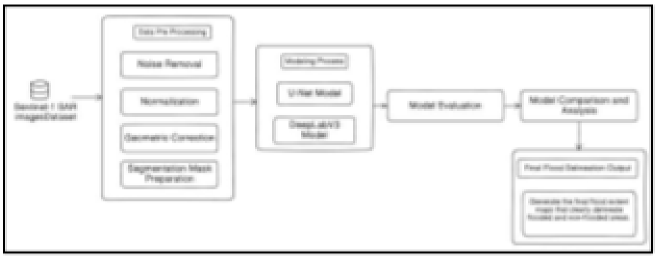


Fig 1: Proposed Architecture

The workflow begins with data acquisition, where SAR imagery is utilized from the Sentinel-1 satellite. These images are chosen for their capability to capture high-resolution data under all weather conditions. This makes them ideal for flood detection.

The next phase is data preprocessing. It encompasses several key steps to prepare the raw data for analysis. Noise removal is applied to mitigate speckle noise inherent in radar images, enhancing the clarity of the imagery. This is followed by a normalization step. It ensures that pixel intensity values are standardized, which is crucial for model performance. Additionally, geometric correction is performed to align the images with geographic coordinates This helps in eliminating distortions from the radar sensors. The final step in preprocessing is the segmentation mask preparation, where ground-truth labels for flooded and non-flooded areas are generated to facilitate model training.

Following data preprocessing, the system enters the modeling process, where two deep learning models, U-Net and DeepLabV3, are employed for segmentation tasks. These models are specifically designed for pixel-level classification and are well-suited to identifying flood-affected regions in SAR images. The U-Net model, with its encoder-decoder structure, captures the context and ensures precise localization, while the DeepLabV3 model employs atrous convolutions for multi-scale context handling, which is particularly beneficial for dense prediction tasks such as flood mapping.

Once the models are trained, the model evaluation phase is initiated, where the performance of both U-Net and DeepLabV3 is rigorously assessed. assessment is done by using metrics such as accuracy, precision, recall, as well as Intersection over Union (IoU)measure. These metrics help quantify the models' effectiveness in correctly identifying flooded regions.

The model comparison and analysis stage follows, where both models are compared based on their evaluation results. This analysis provides insights into which model is more suitable for flood detection in terms of both predictive performance and computational efficiency.

Finally, the system outputs the final flood delineation results, generating comprehensive flood maps that clearly differentiate between flooded and non-flooded areas. These maps are designed to assist in real-time disaster response and resource allocation, aiding governmental agencies and disaster management teams in flood mitigation and emergency planning efforts.

VI. IMPLEMENTATION

A] Evaluating Dataset From Different Geographical Areas

The trained models were then tested on Sentinel-1 flood data from four different geographical areas. The flood events covered in these dataset are described below:

1. Nebraska Floods, USA, 2019

Between March 14 and April 1, 2019, Nebraska experienced significant flooding caused by rapid snowmelt and heavy rainfall. The floods affected over 1,741 square kilometers of agricultural land and urban areas. VV and VH Sentinel-1 imagery pairs were acquired before and after the flooding event. This was then used to map the inundated regions and assess their impact. These images, taken from the ESA Sentinel Hub, served as inputs for model testing.

2. North Alabama Floods, USA, 2019

From February 2 to March 27, 2019, heavy rainfall in North Alabama caused widespread flooding, affecting over 13,789 square kilometers. The prolonged rainfall led to the overflow of rivers, inundating nearby towns and farmland. Sentinel-1 SAR images, collected on multiple dates before and after the flood, were used to evaluate the performance of the flood detection models. VV and VH polarization data were further processed for comparison.

3. Bangladesh Floods, 2017

Bangladesh, a region prone to seasonal flooding, experienced a major flood event between March 14 and July 12, 2017, affecting 7,150 square kilometers of agricultural land. Torrential monsoon rains caused riverbanks to overflow, submerging large areas. To analyze the flood, VV and VH pairs of Sentinel-1 images were captured before and after the flood period. These images were then processed to detect water bodies and flood extents.

These flood representations are observed in fig 2 .

4. Red River North Floods, USA, 2019

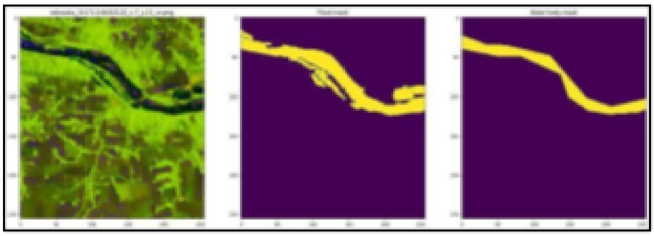
The Red River North region experienced severe flooding between March 14 and April 1, 2019, affecting approximately 6,746 square kilometers. The combination of snowmelt and heavy rainfall overwhelmed the river’s capacity, leading to widespread inundation. Sentinel-1 SAR images, with

VV and VH polarization, were obtained from the ESA Sentinel Hub both before and after the flood. The flood data was processed to create flood segmentation maps.

Data Preprocessing and Analysis:

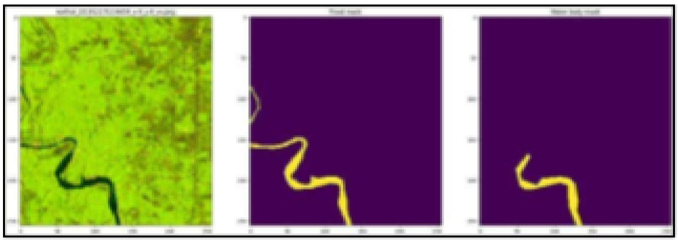
These datasets were chosen to represent diverse flood events, from seasonal monsoon flooding to rapid snowmelt-induced floods. The Sentinel-1 data underwent consistent preprocessing steps.

RGB Image Flood Mask Water Body Mask



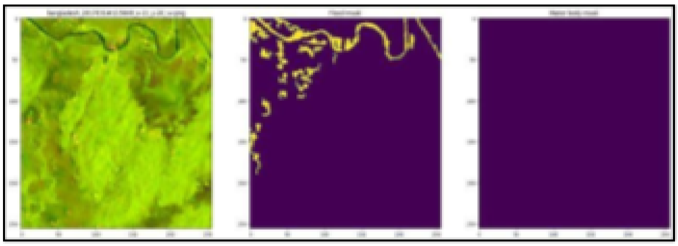
Nebraska Floods, USA, 2019

RGB Image Flood Mask Water Body Mask



North Alabama Floods, USA, 2019

RGB Image Flood Mask Water Body Mask



Bangladesh Floods, 2017

Fig 2 : Different geographical areas

These include radiometric correction and speckle filtering, to ensure compatibility with the training data. Each image was converted into 256x256 pixel tiles, and an additional channel representing the ratio (VV+VH)/(VV−VH) was added to enhance the segmentation accuracy.

The trained models were then applied to both the pre- and post-flood images to detect flood water pixels. Reference water masks, created through hand-labeling with Sentinel-2 data, were used to validate the model's performance. The final segmentation maps were stitched together using a tapered cosine function to minimize border errors.

B] Flood detection using U-Net Model :

The U-Net model, introduced by Ronneberger et al. (2015), has been widely utilized in various image segmentation tasks. This is done owing to its symmetric architecture and effective localization capabilities. U-Net is particularly well-suited for flood detection from satellite imagery due to its ability to capture both high-level semantic information and detailed spatial features. In the context of flood detection, the model processes Sentinel-1 SAR images, a popular dataset in remote sensing, to perform pixel-level classification, distinguishing between flooded and non-flooded regions. The UNet's architecture consists of two main paths: the contracting (encoder) path and the expansive (decoder) path.

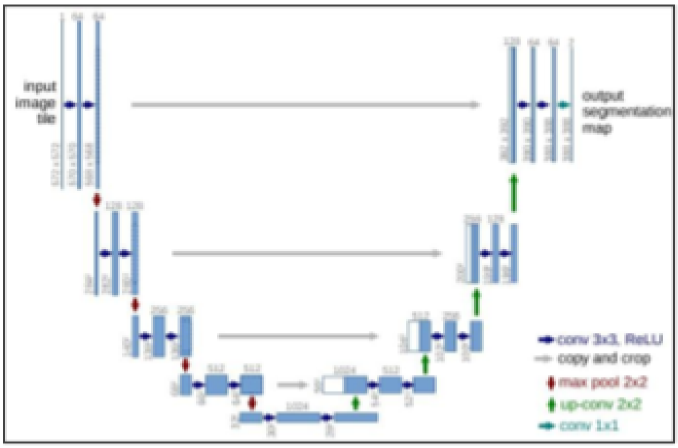


Figure 2: Visualization of U-Net Model. (source: U-Net paper)

The contracting path extracts feature maps from the input SAR images through a series of convolutional layers followed by max-pooling operations, progressively downsampling the input to capture the semantic essence of the flood data. The expansive path, on the other hand, reconstructs the high-resolution segmentation map by performing upsampling and convolutional operations. A crucial feature of U-Net is the use of skip connections between the contracting and expansive paths, which enable the model to combine the spatial information lost during downsampling with the semantic information gained from deeper layers. This synergy allows for more accurate delineation of flood boundaries, essential in flood detection applications.

1. U-Net with ResNet34 Encoder:

The U-Net architecture was implemented with ResNet as the encoder, leveraging its deep residual learning framework. ResNet is known for its ability to handle deeper networks by using skip connections within the layers of the encoder itself, which helps in mitigating the vanishing gradient problem. ResNet's identity mappings allow the U-Net model to learn more complex features from the flood dataset while maintaining computational efficiency. ResNet's pretrained weights on ImageNet provide a solid initialization, helping the model converge faster when applied to Sentinel-1 SAR data. This combination of U-Net and ResNet allows for the extraction of multi-scale contextual information critical for flood detection tasks, improving the accuracy of delineating flooded regions.

2. U-Net with MobileNetV2 Encoder:

MobileNetV2, a lightweight neural network architecture, offers an efficient alternative for flood detection when computational resources are constrained. By employing depth wise separable convolutions, MobileNetV2 significantly reduces the number of parameters and computational load while maintaining robust feature extraction capabilities. When integrated into the U-Net model, MobileNetV2's encoder enables efficient flood segmentation with a focus on real-time applications, such as in drone-based or edge-device flood monitoring systems. Although it may not extract as detailed features as deeper encoders like ResNet34 or DenseNet121, MobileNetV2 provides sufficient accuracy to detect flood patterns, especially in resource-limited settings. This makes it ideal for rapid flood detection systems that prioritize speed and efficiency over the highest possible segmentation accuracy.

3. U-Net with DenseNet121 Encoder:

DenseNet121 is a densely connected convolution neural network that introduces a unique approach to feature propagation by connecting each layer to every subsequent layer. This dense connectivity enables the U-Net model to reuse features across layers, improving gradient flow and optimizing feature learning. In flood detection tasks, DenseNet121 excels by capturing detailed flood patterns across varying scales, making it suitable for both subtle and extensive flood detection scenarios. Its encoder architecture ensures efficient use of computational resources while maintaining high segmentation accuracy. By allowing features to propagate through the network more effectively, DenseNet121 helps U-Net produce precise flood maps, making it especially useful in applications where fine-grained flood delineation is required. This balance of performance and computational efficiency makes DenseNet121 an excellent choice for complex flood detection scenarios where accuracy and detail are crucial.

C] Flood Detection using DeepLab V3 Model :

DeepLabV3 is another state-of-the-art model used in semantic segmentation tasks, and its application in flood detection has gained attention due to its atrous (dilated) convolution and pyramid pooling techniques. These mechanisms allow DeepLabV3 to capture multi-scale contextual information while preserving spatial resolution, a critical aspect when dealing with high-resolution satellite images like Sentinel-1 SAR data. The model operates by encoding the input image through a series of convolutional layers with dilated convolutions, which help expand the receptive field without losing resolution. The encoded features are then decoded to produce a high-resolution segmentation map that delineates flooded areas from non-flooded ones.

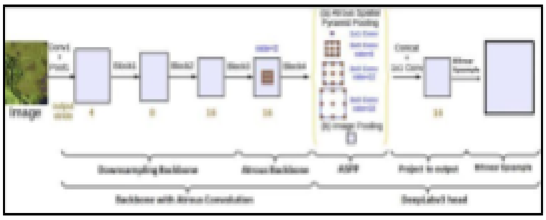


Fig x: Visualization of the DeepLab v3 Model

1. DeepLabV3 with ResNet Encoder

ResNet101, a deeper variant of the ResNet family with 101 layers, serves as an effective encoder in the DeepLabV3 model for flood detection. The depth of ResNet101 allows for the extraction of highlevel semantic features, which are crucial for distinguishing flooded from non-flooded areas in complex environments. The residual connections in ResNet101 enable the model to maintain gradient flow across its many layers, preventing the vanishing gradient problem and allowing the network to learn more nuanced and detailed features from the SAR images. In the context of flood detection, DeepLabV3 with ResNet101 excels at capturing large-scale flood patterns and complex flood boundaries, making it a strong candidate for applications that require a high degree of segmentation accuracy. However, the depth of ResNet101 means that this configuration may demand more computational resources, making it suitable for environments where computational power is not a limiting factor..

2. DeepLabV3 with MobileNetV2 Encoder

When paired with the MobileNetV2 encoder, DeepLabV3 becomes a highly efficient model optimized for flood detection in resource-constrained environments. MobileNetV2's use of depthwise separable convolutions reduces the model's parameter count and computational requirements. Thus, it makes it ideal for real-time flood monitoring applications where speed and efficiency are critical. Despite its lightweight design, MobileNetV2 retains the capacity to extract meaningful features from SAR data. This allows DeepLabV3 to perform accurate flood segmentation with minimal computational overhead. This further makes the DeepLabV3-MobileNetV2 combination well-suited for flood detection systems. It can further be deployed on mobile or edge devices such as drones or remote sensors. This configuration offers a practical solution for scenarios where real-time detection and efficiency are prioritized over the highest possible precision. VII. RESULTS

This section of the paper, presents the results of our implementation for flood detection using U-Net and DeepLabV3 models along with their respective encoder configurations. The following results demonstrate the performance metrics obtained from our experiments. It provides insights into the efficacy of each model and accurately identifies flooded regions in Synthetic Aperture Radar (SAR) imagery. Through this analysis, we aim to highlight the strengths and weaknesses of the various model configurations, contributing to a deeper understanding of their applicability in real-world flood monitoring scenarios.

Metric	Accuracy	Precision	Recall	F1 Score
UNET - Resnet34	0.99	0.86	0.23	0.36
UNET - Mobilenet_v2	0.97	0.30	0.21	0.19
UNET - Densenet101	0.99	0.84	0.30	0.43
DeepLabv3 - Resnet101	0.99	0.87	0.28	0.41
DeepLabv3 - Mobilenet_v2	0.99	0.73	0.31	0.42

Table 1 : Comparative Analysis of Evaluation Metrics

Table 1 provides a comparative analysis of evaluation metrics for different encoder configurations used in U-Net and DeepLabV3 models. It specifically focuses on accuracy, precision, recall, and F1score. It shows that most models achieve high accuracy, with UNet-ResNet34, UNet-DenseNet121, DeepLabV3-ResNet101, and DeepLabV3-Mobilenet_v2 all reaching an accuracy of 0.99, while UNet-Mobilenet_v2 shows a slightly lower accuracy at 0.97. The precision values vary significantly, with DeepLabV3-ResNet101 and UNet-ResNet34 exhibiting higher precision (0.87 and 0.86, respectively), suggesting these models are more effective at minimizing false positives.

In contrast, UNet-Mobilenet_v2 has a lower precision (0.30), indicating more false positive predictions. Regarding recall, the values are generally low across all models, with DeepLabV3Mobilenet_v2 achieving the highest recall (0.31), indicating better capability in identifying true positive cases. UNet-DenseNet121 achieves the highest F1-score (0.43), suggesting a good balance between precision and recall. This analysis highlights the trade-offs between precision, recall, and overall accuracy, providing insights into the strengths and weaknesses of each model configuration for flood detection tasks.

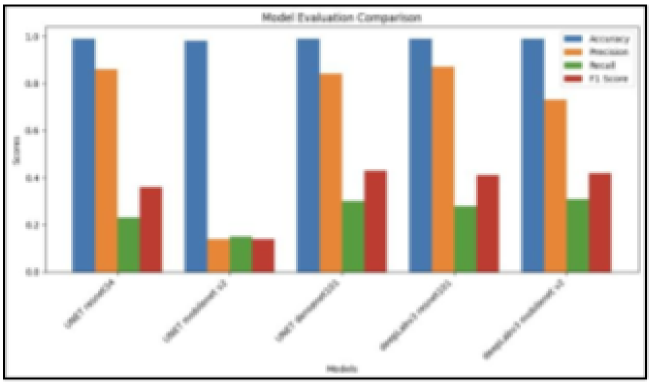


Fig 3 - Model Comparison Bar Graph

The bar chart , represented by fig 3, presents a comparison of key evaluation metrics—accuracy, precision, recall, and F1-score—for different encoder configurations of U-Net and DeepLabV3 models. All models display high accuracy, particularly UNet-ResNet34, UNet-Densenet121, DeepLabv3-ResNet101, and DeepLabv3-Mobilenet_v2, which have nearly perfect accuracy scores. Precision varies more, with DeepLabv3-ResNet101 and UNet-ResNet34 having notably higher precision, indicating better identification of true positives. Recall values are generally lower across models, suggesting a challenge in capturing all positive cases. UNet-Densenet121 has the highest F1score, indicating a balanced performance between precision and recall.

The ROC curve, indicated by fig 4 evaluates the classification performance of various U-Net and DeepLabV3 models. It evaluates by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR). The AUC (Area Under the Curve) values reflect each model's ability to distinguish between classes, with DeepLabv3 using MobileNet_v2 achieving the highest AUC.

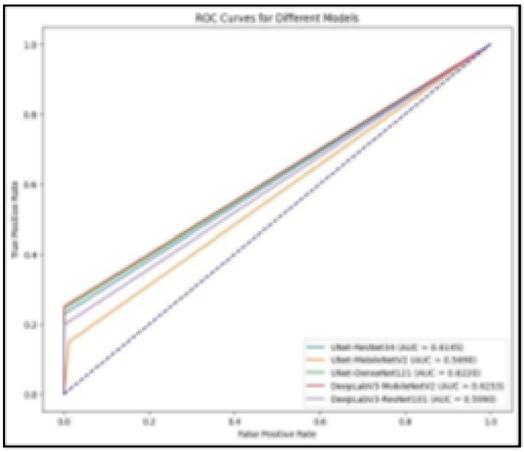


Fig 4 : ROC Curves for Different models

In contrast, UNet-ResNet34 and DeepLabv3-ResNet101 have lower AUCs (0.6145 and 0.5990, respectively),suggesting reduced effectiveness in identifying flooded areas. (0.6253), indicating superior classification performance. Overall, the curves highlight the trade-offs between sensitivity and specificity for each model as represented in fig 5.

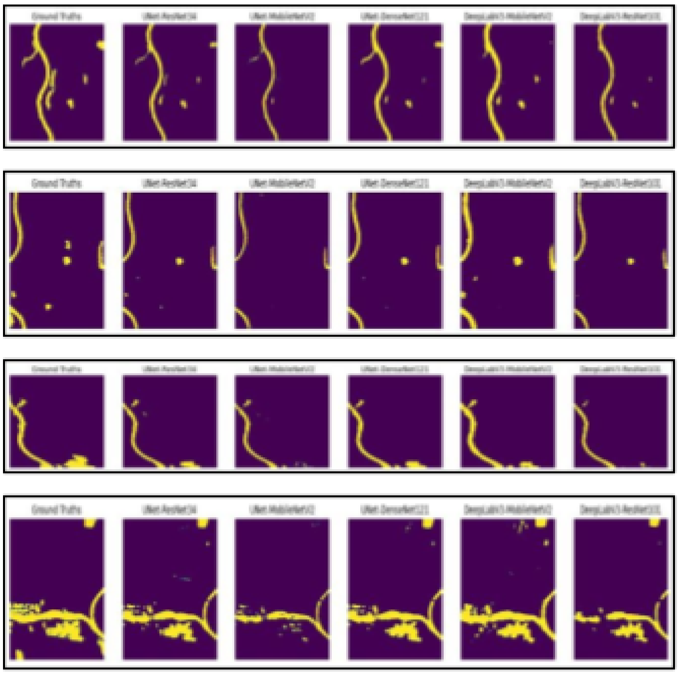


Fig 5 : Model Predictions given the Ground Truth Images

VIII. Conclusion

This paper presents a detailed evaluation of U-Net and DeepLabV3 architectures with various encoder configurations for flood detection using Synthetic Aperture Radar (SAR) imagery from Sentinel-1 satellites. , reflecting a good equilibrium between precision and recall. While the recall values were generally low across most models . This indicates a challenge in capturing all positive instances, DeepLabV3-Mobilenet_v2 and UNet. DenseNet121showed better recall performance .

DeepLabV3-Mobilenet_v2 and UNet-DenseNet121 showed relatively better recall performance, suggesting they might be more effective when the emphasis is on capturing every flooded area.

All models achieved high accuracy (around 0.99) except for UNet with MobileNet_v2 (0.97), which had slightly more misclassifications. The work revealed that model selection depends on the specific needs of flood monitoring applications. It relates to determining whether the focus is on reducing false alarms, enhancing sensitivity, or balance both aspects for general-purpose use.

This research underscores the effectiveness of using SAR data for flood detection under diverse weather conditions, Our models partially address the challenges of noise interference in urban and vegetated areas. There is however a scope for refining noise handling and improving the delineation of flood boundaries in complex terrains. The results of this study provide a foundation for future improvements in automated flood detection, offering a robust framework that can be iteratively enhanced for real-time and large-scale flood monitoring. This research aims to advance flood detection technologies, contributing to early warning systems that can save lives and resources in flood-prone regions

VIII. Future Scope

Future research can focus on integrating multi-sensor data fusion by combining SAR with optical imagery and Digital Elevation Models (DEMs) to improve flood detection in complex terrains. Enhancing computational efficiency for real-time flood detection is another critical area, which could be achieved through lightweight models and cloud-based processing. Additionally, advanced noise reduction techniques for SAR data could improve accuracy in urban and vegetated areas. Exploring unsupervised and semi-supervised learning approaches can reduce the reliance on labeled data, making the system more adaptable. Finally, real-world implementation and integration with early warning systems will be key to operationalizing the technology for disaster management.

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